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ETHNICITY CLASSIFICATION FROM FACIAL IMAGES USING DEEP LEARNING METHODS

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Abstract

Ethnicity classification from facial images is a vital task with broad applications in domains such as mental health diagnostics, demographic analysis, human-computer interaction, and social behavior modeling. This study presents a deep learning-based framework for robust ethnicity classification by leveraging facial expression features. The proposed method employs a Convolutional Neural Network (CNN) to extract deep spatial features from facial images, enabling the recognition of seven key facial expressions—happy, sad, neutral, anger, disgust, fear, and surprise—as intermediate attributes contributing to ethnicity identification. Extensive experiments were conducted on publicly available benchmark datasets, demonstrating superior performance over existing techniques. The model, trained using an unsupervised deep feature learning approach, achieved a high average classification accuracy of 95%, indicating its effectiveness and generalizability. The findings suggest that parsing facial expressions can significantly enhance the accuracy of ethnicity classification and support further research in affective computing and biometric identification.

INTRODUCTION

Since the last decade, deep learning has introduced itself as an attractive and interesting area. It also supports a wide range of research topics. Machine learning has different algorithms, while deep learning is one of them. Deep learning has several variants. These algorithms receive inputs, process these inputs using multiple-layered architecture and produce the desired output. These multiple layers, also known as a neural network, consist of different levels. Deep neural networks extract special features and information using learned algorithms. Deep learning models also work as greedy model; it means it will learn from extracted feature from multiples layer. Latest research is depending on facial images pixel space, but there is a great variability having same set of ethnic origin, there is a problem for system to identify the ethnic category of peoples. Machine learning based classification has successfully applied for this problem. Researcher used Discrete landmark model (Lv, Wu, Wang, Dan, & Zhou, 2020).

These methods are based on the numerical value calculating from image pixel space or discrete set of class labels using known relationship from trained images. Human behavior can change with respect to geography ,age and emotions (Latinwo, Falohun, & Omidiora, 2016). In research area of computer vision the most studied topic is face analysis. Using a person's face, we can extract features to estimate the race and ethnicity. Gender and ethnicity are involved in human face perception and recognition (K. Asghar, Gilanie, Saddique, & Habib, 2017a; Attique et al., 2012; Bajwa, Shah, Anwar, Gilanie, & Ejaz Bajwa, 2018; Gilanie, 2013; Gilanie, Attique, Naweed, Ahmed, & Ikram, 2013; Gilanie, Bajwa, et al., 2018b; Gilanie, Ullah, Mahmood, Bajwa, & Habib, 2018b; Janjua, Andleeb, Aftab, Hussain, & Gilanie, 2017; Janjua, Jahangir, & Gilanie, 2018; Hafeez Ullah, Batool, & Gilanie, 2018; H Ullah, Gilanie, Attique, Hamza, & Ikram, 2012; H Ullah, Gilanie, Hussain, & Ahmad, 2015). A lot of effort has been spent on ethnicity classification using facial images using different techniques. Most of them work on a single image. Only a few researchers are focused on images containing multiple objects. Humans present clear demographic traits which allow their peers to recognize their gender and ethnic groups as well as estimate their age (Xia, Amor, & Daoudi, 2017).

Ethnicity is focusing especially on people to use for discrimination between multiple areas of peoples from different countries. Many organizations use this research to judge the locality of the subject. Researchers also work on this subject in 2019 using Support Vector Machine (SVM), ethnic identities as subset of identity category in which eligibility for membership is determined by attributes are associated with descent. This paper explores the difficulty of performing automatic demographic prediction on the East Asian population (Srinivas et al., 2017). Researchers also introduced the range information of human using Support Vector Machine (SVM). For extraction of features, the researchers used Kernel Principal Component Analysis (K-PCA) and Kernel Linear Discriminant Analysis (K-LDA). Result using (PCA) are obtained 94% accuracy with recognition time (RT) 10.02 seconds. Using (LDA) accuracy obtained 97.33% with recognition time (RT) 10.11 seconds (Attique et al., 2012). Researchers identify six levels of ethnicity for data (Villarroel, Davidson, Pereyra-Zamora, Krasnik, & Bhopal, 2019) .Important topic of face recognition are race and ethnicity. In fact human face gave us variety of information that can be used for different classification like age, race, gender and ethnicity. Face's feature are dominant in race classification.

Some important concepts are used for ethnical classification using images. First one is race. Race is a concept which differentiate demographic features i.e. hair, eyes and skin color from face structure. Second one is nation (Gilanie et al., 2013). Nation based on social oriented concepts which refers to different areas. Third one is ethnicity. Ethnicity describe the group of people whose relation is close and have same gene and culture. Their language have geologically close association. Human faces contain large amount of information in biometric form (Gilanie, Bajwa, et al., 2018a). Facial ethnicity can accomplish in few main steps i.e. facial feature's extraction and facial classification (H Ullah et al., 2015). There are many proposed method for features extraction and different classifier. These classifier are used to extract demographic information related to facial images. Local binary patterns (LBP), Gaber filter response, selection and transformation methods to enhance the results of subject. Finally used k- nearest neighbors

(KNN) and support vector machine (SVM) receiving multiples images as input and categorized in different ethnicities (H Ullah et al., 2012).

Cognitive method gives reliable accuracy (Kandt & Longley, 2018). Human brain can identify the ethnicity, age and gender discrimination using some information (K. Asghar, Gilanie, Saddique, & Habib, 2017b). In the past many researchers have worked on facial ethnical recognition to get reliable facial characteristics by employing various methods like geometric shapes (Gilanie, Bajwa, Waraich, & Habib, 2019b). Researcher extract geometrical facial feature i.e. Height and length of nose, underjaw's shape and measure the mouth. Although Sparse Representation is immensely useful in facial identity, but it is useless in racial identity (Gilanie, Ullah, Mahmood, Bajwa, & Habib, 2018a). Especially when facial characteristics are illustrated of small racial group (Gilanie, Bajwa, Waraich, & Habib, 2019a). Different measures are used to recognize ethnicity using sparse sensing first one is (K-NN)(Janjua et al., 2018) .It is established on sparse perception in order to recognize racial group, second is whole racial facial characteristics and third is Salient ethnic region extraction (Gao, Zeng, Bai, & Shu, 2020).

The enhancement in electronically instrument and link of human with software application are totally based on how much year old a human and facial expression (Villarroel et al., 2019). For obtaining required information many researcher use the facial extraction feature algorithms(Janjua et al., 2017). Facial feature are compulsory extracted because its major feature to identify the ethnicity (Gilanie, Bajwa, Waraich, Asghar, et al., 2021). To achieve the required result or milestones feature exploration must be compulsory because without exploring the feature our results cannot achieved and our efforts are useless (Rafiq, Bajwa, Gilanie, & Anwar, 2021a). Many things are identify through the face features (Lakshmiprabha, 2016). Age is identified through exploration of feature of face with different angles of images (Rafiq et al., 2021a). Nose are helpful for this purpose (Gilanie, Nasir, Bajwa, & Ullah, 2021). Nose length, their texture and width are main used parameter to find out our age estimation object. Now a day's linkage of human with device are increasingly day by day (Gilanie, Bajwa, Waraich, & Anwar, 2020). Computer vision is as fast as like human. Devices are being learned to treat as like human. Now a days machine are able to abstract the decision from given information or can decide any action to see the environment (Gilanie, 2019). If machine is capable to achieve the expression behavior and other activities which are related to human then it's a friendly environment between machine and human (Tippu et al., 2017). This a big revolution in the computer vision history (Bajwa et al., 2018). When machine is capable of doing the change in feature or in task performed by human then these era of computer science can achieve maximum concentration. This change leads many researcher to putt maximum effort to access attributes from the devices (Hafeez Ullah et al., 2018). Face is a object which features are changed with the passage of time. Face helps the researcher to explore many problems even all problems which can be solved with the help of facial images (Janjua et al., 2018). If facial feature are not mature then it's a big problem and very difficult to identify the feature of ethnicity, age and gender. The problem of identifying the work. If images of same race then it is easy to identify the race and if images are from any other race then it seem to be similar of one race but those images are different from one another but our proposed model can differentiate these images very easily. The system trained in manner that some different images of different races are used for training and give input of any images to identify that specific images are belongs to which ethnicity.it is easy to identify the American than Asian because American climate is different from Asian therefore it's easy to differentiate the ethnicity. Some methods are work on special images and other work on different subject of images. If we design the model for color images then it also execute the color images while if we design the model for black images them it also execute the black images, But here is a problem if there is color images and model is available that is for black images then there is big issue then have to develop the application that can process both black and colored images. For this purpose researcher used the some process. Researcher collect the images. After collecting the images of different subjects then it necessary things is to train the images which we to collect. Training process depend on number of images as number of images are exceed then training process must be efficient. Model exclude the noise from the images and remove noise after doing this separate the objects contained in the images. Model extract the feature from images. After this model match the attributes with trained images if match then give output into some subject. Images of any person vary with respect to time and effect food, air and other health issues. Physically this change are different with person to person so face is nonlinear in changing the feature (Gilanie, 2019; Gilanie, Bajwa, Waraich, & Anwar, 2021; Gilanie, Bajwa, Waraich, Asghar, et al., 2021; Gilanie et al., 2019a, 2019b; Gilanie, Javed, et al., 2021; Gilanie, Nasir, et al., 2021; Gilanie, Saher, et al., 2021; Malik et al., 2021; Rafiq, Bajwa, Gilanie, & Anwar, 2021b). It is a compulsory to find out the estimation of age, find out the behavior of person like talking truth or lie or our particular output to find the race and ethnicity of person using facial images so that our application must work automatically to carry the task performed by human in machine for information to take decision related to any activity. Race of people are publically type of people which are represented by one another beyond some inheritably features. These people familiar with each other and another are commonly differentiated by their living style and neighbor people (Latinwo et al., 2016).

Images provides us a facial information about race and sex that what images are male or female and images belong to which ethnicity, because it is important to know either person is male or female and images which we have to check belongs to which ethnicity. Different approaches are used to solve the appropriate issue regarding ethnicity. People easily understand the race of people through seeing the human face images. For understanding any subject related to face feature then images of face provides a vital role to predict the race, ethnicity and how much year old. Psychologists pass a statement about some people who done any misbehave with other one then he try to change their identity. In the field of computer science and computer vision this problem is addressable for researcher to take risk on this topic to evaluate how they can find out the ethnicity and which facial feature are used to evaluate the ethnicity and race of people using facial images. However researcher use different technique to implement this idea. Once model of identifying the ethnicity is develop then it can be used till many year because ethnicity of person cannot be changed throughout the life. It also helpful to identify other related facial features that belongs to face of human. Researcher made a model that using any extracting algorithm which extract the texture of given images of face.in this complete texture we segregate the skin area from the images from colored area then model separate the skin area and other area. Give the pixels values to both skin and other area without skin area respectively. After this skin values are further classified and pass to any layer of neuron. Images are used input as input in proposed model, these input images are further into different layers using convolutional neural network (CNN). Iteration of different layers generate the bias value. Extract the face from given images and extract required face features i.e. Nose eyes and lips etc. using different pattern to separate the image of part that contains skin area and further processing on it. While separate the nonskid area that is not our requirement. Skin area are helpful for identifying the ethnicity. Nonskid area belongs to hairs that cannot a used to identify the ethnicity (Akhtar et al., 2025; Amjad et al., 2021; Amjad, Ullah, Siddique, et al., 2025; Amjad, Ullah, Ullah, et al., 2025; Anwaar, Gilanie, Namoun, & Sharif, 2025; Bagchi, Amali, & Dinakaran, 2019; Gilanie, Abbas, et al., 2025a, 2025b; Khera et al., 2023).

Information of death record can maintained the death rate in any country so ethnicity may help to find out country death rate. When we find out ethnicity of dead body with the help of images that can perceive information about which ethnicity the dead body belongs. Death rates are compulsory for the evidence of heath department and also important factor for mortality. It can be consistent only if the census population is accurate and consistently. Its depend on the human who gave the information the mortality and ethnicity, if reporter person gave illegal and wrong result to a data collector then output is not in the form of consistent therefore the report of different every month. If we want to produce consistent information about death rate then we should have to manage the structure of collecting data. We use multiple resource for collection of consistent data (Das, Dantcheva, & Bremond, 2018).

Machine learning have technique to find out the ethnicity name which he knows using any public data that are available on internet or public source. This approaches is differ from other proposed techniques in many aspects. It works beyond on multiple unit of images. There is no need of extracting the feature or not to train the model. The proposed model take the instance of name writer and system check their country name, when country name is find then its more easy to identify the ethnicity of instances (Torvik & Agarwal, 2016).

Now days mobile are mainly used in real world. Every person knows the use of mobile very well and also mobile have the ultra large scale memory size so now a days it is a great edge for the computer scientist to develop a model for mobile user in appropriate environment that must be capable for doing large scale application such as finding the ethnicity age and gender. Mobile have minimum risk of security therefore for the researcher it's a new domain introduced in computer vision that can be used without any security risk, even a also a new idea to improve the person believe or mobile user 's trust on mobile by improvement of issues regarding security (Ghaffar et al., 2022; Gilanie, Asghar, et al., 2022; Gilanie, Rehman, et al., 2022; Iqbal, Bajwa, Gilanie, Iftikhar, & Anwar, 2022; Rubab et al., 2022; H Ullah et al., 2022; Wazir, Gilanie, Rehman, Ullah, & Mushtaq, 2022; Yaseen et al., 2022). when security issues are minimize then a huge number of mobile user can user rely totally on mobile based application that are related to different domain of research. Bio metric is also a newly introduced and dominant in the market that is domain of computer science. Uses of bio metric machine having no security issues have a large number of model that implement finger print machine like in hospital airport nadra offices land record offices and attendance system of school college and universities etc. From the previous some decade, racial identification is understanding the major research topic of finger print device and identification of person in different perspective from images of human face. This research topic is add in the category of soft electronic research area. When we add it into a soft electronic research area then researcher must have to enhance the security .When security are maintained then it can be add in mobile compatible software, this task is challengeable for the researcher. This research is challengeable when there is memory issue because large scale memory used for this proposed model but now a days memory problem is resolved it means researcher can easily convert it into mobile application. Mobile application take input as finger scan or selfie or images then further processing are executed to extract the required result in the form of ethnicity. Researcher combined the model to produce the output in a way that images can be execute on device like mobiles. Earliest task that the researcher develop with the combination of area of skin and shapes to discriminant the sex of human and race but in that research there are some drawback that researcher's model just identify the two classes of ethnicity i.e. pure black and pure white. Still another problem is that similar type of research is done by many other researcher with the difference of accuracy point. A researcher published a paper on ethnicity of different classes in 2017. He proposed a model that could identify the black white and also some other classes. Above drawback should be cover in 2017 published paper on ethnicity classification of various classes using (CNN). This published paper accuracy is 98.5 %, experiment done using online public dataset. There is new invention for the identifying the type of images. This newly designed approaches cover the problem related to the limited identification of ethnicity because before this just two subject of ethnicity can be identified. Main advantages of proposed model is to generate the output in the form of identifying the types classification in less time rather than other proposed model of identifying the ethnicity of classification. This proposed model are used the framework of (CNN).It give output of proposed model efficiently and accuracy is very high. This proposed model use the (CNN) for classification, it takes those images as input for processing that images are able to process through graphical processing unit. These pictures are for identification of electronically hand written because these images are use minimum memory and computational time for processing If someone wants to compare these images then it should be compulsory that his/ her system have graphical processing unit because it model is specially designed for graphically processing unit. No doubt when we compare the images for ethnicity classification then we checks results of other processor for giving instances of datasets on simple processor, the result of simple processor are compiled and we write it. After this we cheeks the results from same number of instances of dataset which we use for simpler processor, now we check on graphical processing compiler. Result of graphical processing compiler must be highly remarkable. The vital role is of (CNN) for developing the mobile based application (Mohammad & Al-Ani, 2018). Uniquely depiction of human are used everywhere now a days in our routine life assignment. Unique identification is compulsory whenever we want to do any task like we want to do a transaction regarding our bank account there we must have to use our identity like bio metric identification or using our debit card we must have to enter special protected keyword. When we visit in hospital for any treatment or for medical test then we must have to use our personal identification like identity number or bio identification. When we want to open our email address we should have to enter our password and so on (Oluwatobi & OFW, 2019). Roma is a community which are non-Muslims is their ethnicity belong to Europe. Roma community is considered as minorities there. The point which come to notice that data which are provided is not a valid with respect to accuracy therefore many confliction are exist in many record or doing any survey, newly generated report are not considered a valid or economy or population are not considered good due to incompleteness of data. Some researcher took a concentration on this major issue of Roma community to solve the issue regarding many problems. There is need of research which use actual datasets. Because these all problem can be solved to identifying the ethnicity, gave accuracy about to hundred percent. Research also give a systematic mobile embedded or biometric framework for collecting any information. For solving the research gap the researcher, collect the largest data related to ethnicity in whole country of Europe (Afzal et al., 2023; M. Ahmed, Gilanie, Ahsan, Ullah, & Sheikh, 2023; S. Asghar et al., 2023; Batool & Gilanie, 2023; Ghani & Gilanie, 2023; Gilanie, Bajwa, Waraich, Anwar, & Ullah, 2023; Hafeez et al., 2023; Khera et al., 2023; Nazir et al., 2023; Shafiq, Gilanie, Sajid, & Ahsan, 2023; H Ullah, Batool, Nazir, Akhtar, et al., 2023; H Ullah, Batool, Nazir, Mohsin, et al., 2023; H Ullah, Zafar, et al., 2023). Researcher takes advancement in both written documentation and proposed intelligent model that could auto identify the ethnicity of just Roma community. Another issues issue are still not solve that dataset of Roma community is not enough that a system can be trained very well because good result are deployed on good proposed model and having a large amount of data sets that a system can be trained very well .The term large amount of datasets refer to actual dataset with appropriate ethnicity. Everyone knows that results of doing survey involving small data, good characteristics of output are not achieved. If framework of model cannot be reapprove then these flaws are remain same. There are no consistent methods that can be applied that can be used to evaluate reports of Roma community, if we compared the Roma and non Roma community then result would be better than other, reason is this that non Roma community have large datasets and have actual dataset using different source to collect the datasets. Many peoples are considering this Roma are included in general census that is based on visible feature but Roma people are not included in population so many researcher get the data of general census and makes experiment, therefore dataset not match with Roma people then results are not good, So they can now use a method to collecting dataset they take an interview. Before this ethnicity identification done using name and external behavior this feature are not valid for ethnicity. There are two methods which are used to identify the ethnicity among many people of different ethnicity i.e. self-related data about persons and external traits of person. If we compare the both then external traits are helpful to identify the ethnicity and output are valid than self-related data. These confliction in results of same person is due to lack in proposed code that give us two results of same dataset. It means that there are lack of concentration of viewer for gathering traits of persons (Janka, Vincze, Ádány, & Sándor, 2018).

In daily works of life different person evaluate the racial, how much old of people and other feature extracted that are necessary for daily routine work. Many previous research from multiple paper it has been observed that how classification can be done using different model with different datasets.

Normally study related to the face have demonstrated that from facial images ethnicity can be identify properly having no confliction. Results are true up to the marks from previous study. According to previous study doing experiment on images of male and female, it has been observed that male images have good result as compare to female images. Reason is this male face feature are much more mature than female face features. Some feature make more prominent male from female likewise nose length is greater than female that can easily predictable than female nose length. Back side of head of male person are like straight and female head back side are not straight this a big difference between male and female features. The side of eyebrow is totally different of female eyebrow from male eyebrow. The most differential feature of face is texture of female is totally different from male because skin of male is hard than that of female face skin. Sometimes size of man's eye are different from female's eyes. The nose and upper lip of man is less far as compared to female because female distance is much more than that of male lip distance. All of above describe differences are clearly demonstrate the male images are high output than female face images. The views of researcher are that from the people of north side have longer nose and thicker lips that clearly defined the ethnicity. It has been noticed that a person having huge or expanded face having the high age. When the age of person is between eighteen year to twenty year then its face are different as when his/ age is twenty eight to thirty years old. Face are small as in twenty year and broad than in as thirty year. So for this feature of age is identified easily the age of person using face images. From a previous decade, working on images are frequently enhance day after day. New model are develop to work on images based to identify the ethnicity. The maximum works has been done on colure based images. Because color images have clearly feature contained in the particular area of images. If we use black and white images then there visibility of features are not clear as compare to color images (Xia et al., 2017).

As we know the feature are inherit from previous generation to next generation if we knows about the previous generation record then we automatically identify the ethnicity of next generation. Because the feature are inherit as same to the next generation. Some of feature are symmetric which belongs to the face images. It's an experiment that we take the images of parent generation to check weather its output related to the ethnicity is correct or not if his/her ethnicity is correct then we have to do another task on same proposed model. We take images of child of that parent which ethnicity check before. After execution of the proposed model results generate. Now we check whether the results of parents are same as the result of child. If both results are same regarding to ethnicity it means parent ethnicity feature are also inherit in their child if they are in same continent (A. Ahmed et al., 2025; Batool et al., 2025; Gilanie et al., 2024; Naveed et al., 2024; Rashid, Gilanie, Naveed, Cheema, & Sajid, 2024; Saher et al., 2024; H ULLAH, BATOOL, et al., 2024; H ULLAH, GHALIB, et al., 2024). Same inherit is done in female. Method which are used in the past they used the different pattern to identify the face images, on the other side some of researcher make a model that use dimension of face images for the identification of ethnicity using color facial images. In model that use dimension interpret the images using different angles. It checks the image as vertical and extract the feature related and also checks the images as horizontal (Sajid et al., 2018).

The images of face is tool for researcher that are used to identify many things related to human like ethnicity race age and many more things. Ethnicity identification is from those topics which are most important and have a popularity in recognition or identification of person behavior using demographic features. As globalization increase day by day recognition face component are mainly used at airport some security purpose and for intelligence agencies. For some important measures it becomes important research domain area. Normally images of face are change by the things which he/she used or the place where he/she lived. Ethnicity feature cannot be changed easily because same ethnicity have many area of people so it's a more difficult to change the ethnicity of any object cannot be changed. Some of peoples have their same ethnicity where one ethnicity area have ending area and other ethnicity area are started. There is big challenge for the researcher to uniquely identify the ethnicity of same areas of peoples belongs to closed area of ethnicity. Because living style of both ethnicity people. Although living style of people are common but they have some unique feature in their face images that differ from one another to others. If these person seen by human it is difficult to differentiate a person belongs to which ethnicity but model can be trained in a way that if all face feature are same except one , the system can automatically identify the ethnicity. In Pakistan there is a big issue when we do experiment of Gilgit, Chitral and their covering area's people and want to identify the ethnicity or race then difficult to identify because these area of people same as like China and Pakistan. Some of researcher make the system that identify the ethnicity and also show the percentage of ethnicity name. |If subject is Pakistani then it would also describe the particular subject have how many relate to the Pakistanis and how want percent are related to the Chinese. I think it's a new domain area that can also print the percentage of related ethnicity. Using artificial intelligence is compulsory to identify the each feature which are necessary to identify the ethnicity, there are different techniques used for this purpose. But researcher used appropriate pattern to acquire own target for identification or recognition. Researcher used to identify the racial group. Racial group means to identify group of same kind of ethnicity from large datasets. It segregate the similar type of group of peoples that are relate to similar group. How many group are made it depend on researcher to making the subject of output. If researcher make four group of ethnical group than researcher must be collect the four type of datasets like Asian, American, Australian and Chinese. A large number of dataset are required Asian, American, Australian and Chinese. From random number of images model must make group of similar type of racial groups. Here is three terms related to the identification. Race is a term which belongs to structure of human of face like texture nose and all about demographic features. The cast is a term which is community oriented and name suggested by community or environment. Ethnicity is a term which refer to many people and their culture that a living style of group of people. What are the food which they used and how has their texture. Some of researcher have idea about the two things are same except cast. But those ideas are totally wrong because according to definition there are big difference between them. Ethnical members are selected as by identifying similar type of features like nose shape and other demographic feature contained in particular images. No doubt there is miner difference between two term race and ethnicity because they have difficult to identify the difference. In previous study from few decades, there are some representation used to identify the facial expression. Feature of images are not enough for the ethnicity classification if there are size of sample images are too much small. Some of main features contained in every facial images if proposed system extract those features clearly then it would be more easy to recognize the person of ethnicity with high accuracy, if system not be able to doing this extraction of certain facial feature then system output are not up to the mark, Therefore much of images are taken of about thirty years old of human. Every images which contain different traits of human face, different face have same features but proposed system must be able to perceive the multiple information for their own purpose like estimation of age, recognition of different facial expression on behalf of datasets. It's ability of researcher that he/she extract the multiple feature from same images. These images are further processed into multiple ways to attempt or perceiving of required information. In my study of ethnicity some of feature are extracted from given facial images and process it using different type of extraction techniques. These technique using different extraction techniques for extracting particular feature. When extraction is done using different extractor then classifier of different type are used for classification of images. For performing the classification phase's system use some parameter. These parameter specify the certain features contained in a images, different feature such as texture, geometrically form images size of different micro feature. Micro feature are visible feature that are seen by human eyes and any camera of high quality. Remember this similar specification of camera are used for capturing the images. But prefer this a single device are used for capturing the images if we use different cameras for capturing the images than images quality are effected and images are in different size and formats. Although size can be make same of all images but its time consuming process (Gilanie, Batool, Abbas, Cheema, et al., 2025; Gilanie, Batool, Abbas, Latif, et al., 2025; Gilanie, Batool, Abbas, Shafique, et al., 2025; Gilanie, Shafiq, et al., 2025; Kashif et al., 2025; Latif et al., 2025; Sajid et al., 2025; Siddique et al., 2025; J. Yang et al., 2025). Therefore it's a best try to for the researcher that he /she take this similar size of images on priority base. Feature are match with training images randomly selected images by the proposed model. Similar types of different feature contained in multiple images, combine them which are same and start a polling using layer of (CNN). In face images some specific area contain major features related to ethnicity which are most difficult to finding that feature, for this a good proposed model are developed containing all such requirement that are necessary for attaining the required feature for different type of classification and recognition using facial images(C. Wang, Zhang, Liu, Liu, & Miao, 2019).

Computation work on images of face are growing up day after day, therefore face recognition topic is make more important due to maximum study of this subject. Much advancement of the image processing or image recognition still ethnicity is much complex task. But some researcher had been worked on this major issue. With the effort of researcher this complex task mode is converting into a simpler. But it not so easy that every person can understand the complexity of the ethnicity classification. Different approaches are being used for recognition of ethnicity with proper framework. But some use these approaches in a easy to find out the classification that a common person can understand with little bit concentration. Some of researcher have their own approaches that is still not up to the mark. This proposed study is to design in an easy way that it works on black and white images and on color images. The term, which are mainly used that is, invisible feature are extracting with different pattern of classification.

In daily works of life different person evaluate the racial, how much old of people and other feature extracted that are necessary for daily routine work. Many previous research from multiple paper it has been observed that how classification can be done using different model with different datasets.

Normally study related to the face have demonstrated that from facial images ethnicity can be identify properly having no confliction. Results are true up to the marks from previous study. According to previous study doing experiment on images of male and female, it has been observed that male images have good result as compare to female images. Reason is this male face feature are much more mature than female face features. Some feature make more prominent male from female likewise nose length is greater than female that can easily predictable than female nose length. Back side of head of male person are like straight and female head back side are not straight this a big difference between male and female features. The side of eyebrow is totally different of female eyebrow from male eyebrow. The most differential feature of face is texture of female is totally different from male because skin of male is hard than that of female face skin. Sometimes size of man's eye are different from female's eyes. The nose and upper lip of man is less far as compared to female because female distance is much more than that of male lip distance. All of above describe differences are clearly demonstrate the male images are high output than female face images. The views of researcher are that from the people of north side have longer nose and thicker lips that clearly defined the ethnicity. It has been noticed that a person having huge or expanded face having the high age. When the age of person is between eighteen year to twenty year then its face are different as when his/ age is twenty eight to thirty years old. Face are small as in twenty year and broad than in as thirty year. So for this feature of age is identified easily the age of person using face images. From a previous decade, working on images are frequently enhance day after day. New model are develop to work on images based to identify the ethnicity. The maximum works has been done on colure based images. Because color images have clearly feature contained in the particular area of images. If we use black and white images then there visibility of features are not clear as compare to color images (Xia et al., 2017).

As we know the feature are inherit from previous generation to next generation if we knows about the previous generation record then we automatically identify the ethnicity of next generation. Because the feature are inherit as same to the next generation. Some of feature are symmetric which belongs to the face images. It's an experiment that we take the images of parent generation to check weather its output related to the ethnicity is correct or not if his/her ethnicity is correct then we have to do another task on same proposed model. We take images of child of that parent which ethnicity check before. After execution of the proposed model results generate. Now we check whether the results of parents are same as the result of child. If both results are same regarding to ethnicity it means parent ethnicity feature are also inherit in their child if they are in same continent. Same inherit is done in female. Method which are used in the past they used the different pattern to identify the face images, on the other side some of researcher make a model that use dimension of face images for the identification of ethnicity using color facial images. In model that use dimension interpret the images using different angles. It checks the image as vertical and extract the feature related and also checks the images as horizontal (Sajid et al., 2018).

The images of face is tool for researcher that are used to identify many things related to human like ethnicity race age and many more things. Ethnicity identification is from those topics which are most important and have a popularity in recognition or identification of person behavior using demographic features. As globalization increase day by day recognition face component are mainly used at airport some security purpose and for intelligence agencies. For some important measures it becomes important research domain area. Normally images of face are change by the things which he/she used or the place where he/she lived. Ethnicity feature cannot be changed easily because same ethnicity have many area of people so it's a more difficult to change the ethnicity of any object cannot be changed. Some of peoples have their same ethnicity where one ethnicity area have ending area and other ethnicity area are started. There is big challenge for the researcher to uniquely identify the ethnicity of same areas of peoples belongs to closed area of ethnicity. Because living style of both ethnicity people. Although living style of people are, common but they have some unique feature in their face images that differ from one another to others. If these person seen by human it is difficult to differentiate a person belongs to which ethnicity but model can be trained in a way that if all face feature are same except one , the system can automatically identify the ethnicity. In Pakistan there is a big issue when we do experiment of Gilgit, Chitral and their covering area's people and want to identify the ethnicity or race then difficult to identify because these area of people same as like China and Pakistan. Some of researcher make the system that identify the ethnicity and show the percentage of ethnicity name. |If subject is Pakistani then it would also describe the particular subject have how many relate to the Pakistanis and how want percent are related to the Chinese. I think it is a new domain area that can also print the percentage of related ethnicity. Using artificial intelligence is compulsory to identify the each feature, which are necessary to identify the ethnicity, there are different techniques used for this purpose. However, researcher used appropriate pattern to acquire own target for identification or recognition. Researcher used to identify the racial group. Racial group means to identify group of same kind of ethnicity from large datasets. It segregate the similar type of group of peoples that are relate to similar group. How many group are made it depend on researcher to making the subject of output. If researcher make four group of ethnical group than researcher must be collect the four type of datasets like Asian, American, Australian and Chinese. A large number of dataset are required Asian, American, Australian and Chinese. From random number of images model must make group of similar type of racial groups. Here is three terms related to the identification. Race is a term, which belongs to structure of human of face like texture nose and all about demographic features. The cast is a term, which is community oriented and name suggested by community or environment. Ethnicity is a term, which refer to many people and their culture that a living style of group of people. What are the food, which they used, and how has their texture. Some of researcher have idea about the two things are same except cast. However, those ideas are totally wrong because according to definition there are big difference between them. Ethnical members are selected as by identifying similar type of features like nose shape and other demographic feature contained in particular images. No doubt, there is miner difference between two term race and ethnicity because they have difficult to identify the difference. In previous study from few decades, there are some representation used to identify the facial expression. Feature of images are not enough for the ethnicity classification if there are size of sample images are too much small. Some of main features contained in every facial images if proposed system extract those features clearly then it would be more easy to recognize the person of ethnicity with high accuracy, if system not be able to doing this extraction of certain facial feature then system output are not up to the mark, Therefore much of images are taken of about thirty years old of human. Every images which contain different traits of human face, different face have same features but proposed system must be able to perceive the multiple information for their own purpose like estimation of age, recognition of different facial expression on behalf of datasets. It's ability of researcher that he/she extract the multiple feature from same images. These images are further processed into multiple ways to attempt or perceiving of required information. In my study of ethnicity some of feature are extracted from given facial images and process it using different type of extraction techniques. These technique using different extraction techniques for extracting particular feature. When extraction is done using different extractor then classifier of different type are used for classification of images. For performing the classification phase's system use some parameter. These parameter specify the certain features contained in a images, different feature such as texture, geometrically form images size of different micro feature. Micro feature are visible feature that are seen by human eyes and any camera of high quality. Remember this similar specification of camera are used for capturing the images. But prefer this a single device are used for capturing the images if we use different cameras for capturing the images than images quality are effected and images are in different size and formats. Although size can be make same of all images but its time consuming process. Therefore it's a best try to for the researcher that he /she take this similar size of images on priority base. Feature are match with training images randomly selected images by the proposed model. Similar types of different feature contained in multiple images, combine them which are same and start a polling using layer of (CNN). In face images some specific area contain major features related to ethnicity which are most difficult to finding that feature, for this a good proposed model are developed containing all such requirement that are necessary for attaining the required feature for different type of classification and recognition using facial images(C. Wang et al., 2019). Following are the research questions of this research proposal.

- Can we determine ethnicity of a subject from facial images?
- What are the face micro features, which have significant patterns to determine ethnicity of a subject?
- At what extent size, texture, shape and inter distance between face components play role in ethnicity classification?

Following are the objectives of this research-based study;

- To propose a method, which could auto identify human ethnicity from the face of a subject.
- To identify ethnic groups, which go beyond broad categorizations, as well as assessing the degree of heterogeneity/granularity of their ethnic classifications, especially in censuses and population.
- To develop an application used by border control, airports and law and order agencies.

2.0 Literature Reviewed

Some methods are based on the numerical value calculating from image pixel space or discrete set of class labels using known relationship from trained images. Human behavior can change with respect to geography ,age and emotions (Latinwo et al., 2016). In research area of computer vision, most studied topic is face analysis. Using person's face, we can extract feature to estimate the race and ethnicity. Gender and ethnicity are involved in human face perception and recognition. A lot of effort has been spent on ethnicity classification using facial images using different techniques. Most of them are worked on single image. Only few researchers are focused on images containing multiple objects. Humans present clear demographic traits which allow their peers to recognize their gender and ethnic groups as well as estimate their age (Xia et al., 2017).

Ethnicity is focusing specially people to use for discrimination between multiple areas of peoples from different countries. Many organizations use this research to judge locality of the subject. Researcher also work on this subject in 2019 using Support Vector Machine (SVM), ethnic identities as subset of identity category in which eligibility for membership is determined by attributes are associated with descent. This paper explores the difficulty of performing automatic demographic prediction on the East Asian population (Srinivas et al., 2017). Researcher also introduced the range information of human using Support Vector Machine (SVM). For extraction of features, researcher used Kernel Principal Component Analysis (K-PCA) and Kernel Linear Discriminant Analysis (K-LDA). Result using (PCA) are obtained 94% accuracy with recognition time (RT) 10.02 seconds. Using (LDA) accuracy obtained 97.33% with recognition time (RT) 10.11 seconds. Researcher Identify six levels of ethnicity for data (Villarroel et al., 2019) .Important topic of face recognition are race and ethnicity. In fact human face gave us variety of information that can be used for different classification like age, race, gender and ethnicity. Face's feature are dominant in race classification.

Since the last decade, deep learning has introduced itself as an attractive and interesting area. It also supports a wide range of research topics. Machine learning has different algorithms, while deep learning is one of them. Deep learning has several variants. These algorithms receive inputs, process these inputs using multiple layered architecture and produce desired output. These multiple layers also known as neural network consist of different levels. Deep neural network extract special feature and information using learned algorithm. Deep learning models also work as greedy model; it means it will learn from extracted feature from multiples layer. Latest research is depending on facial images pixel space, but there is a great variability having same set of ethnic origin, there is a problem for system to identify the ethnic category of peoples. Machine learning based classification have successfully applied for this problem. Researcher used Discrete landmark model (Lv et al., 2020).

Some important concepts are used for ethnical classification using images. First one is race. Race is a concept which differentiate demographic features i.e. hair, eyes and skin color from face structure. Second one is nation. Nation based on social oriented concepts which refers to different areas. Third one is ethnicity. Ethnicity describe the group of people whose relation is close and have same gene and culture. Their language have geologically close association. Human faces contain large amount of information in biometric form. Facial ethnicity can accomplish in few main steps i.e. facial feature's extraction and facial classification. There are many proposed method for features extraction and different classifier. These classifier are used to extract demographic information related to facial images. Local binary patterns (LBP), Gaber filter response, selection and transformation methods to enhance the results of subject. Finally used k- nearest neighbors (KNN) and support vector machine (SVM) receiving multiples images as input and categorized in different ethnicities.

Cognitive method gives reliable accuracy (Kandt & Longley, 2018). Human brain can identify the ethnicity, age and gender discrimination using some information. In the past many researchers have worked on facial ethnical recognition to get reliable facial characteristics by employing various methods like geometric shapes. Researcher extract geometrical facial feature i.e. Height and length of nose, underjaw's shape and measure the mouth. Although Sparse Representation is immensely useful in facial identity, but it is useless in racial identity. Especially when facial characteristics are illustrated of small racial group. Different measures are used to recognize ethnicity using sparse sensing first one is (K-NN) .It is established on sparse perception in order to recognize racial group, second is whole racial facial characteristics and third is Salient ethnic region extraction (Gao et al., 2020).

Deep learning technique have great changing in progress of computer insight to accomplish duties of sorting pictures, purpose of discovery and facial identifier (Zaghbani, Boujneh, & Bouhlel, 2020). These changes excite researcher to utilize employing Deep Convolutional Neural Network (DCNN) to solve the number of facial ethnicity classification problems (Baig et al., 2019). DCNN are used to learn automatically appropriate feature to classify the ethnicity. Performance computer oriented the useful communication between human language and computer language becomes of paramount importance (Bessinger & Jacobs, 2019). Communication between man and computer is highly refined tool to comprehend precisely man's demographic feature. The most advanced computed might be able to respond as human being do (Kärkkäinen & Joo, 2019).

Racial group comprehension is an important topic to be researched. Before this research effective sparse sensing approach is not efficient to recognize when whole featured face images are used (C. Wang et al., 2019). Researcher used facial figure detector STASM to find important landmark in face image using Minimum redundancy maximum relevance (MRMR) algorithm. Secondly, we use "T" Region in a face for the representation of ethnical features. With the rapid use of people globalization face recognition is used in management of border, custom check and perceive mass safety also used in anthropology. “T” Region is also focused on racial group. It essential to discriminate between three term race nation, and ethnicity. Race denote that it can be expressed by physical structure like hair, skin and so on. Nation shows society with its particular civilization nomenclature and economics while whole ethnicity shows national or racial group of people. Human brain perceptive quality can perceive many information keeping in view past research evaluation in order to obtain facial characteristics by utilizing statistical features.

This study is beneficial regarding the issue of racial division based on their facial characteristics (Masood, Gupta, Wajid, Gupta, & Ahmed, 2018). Dataset which are used in this model is Mongolian, Caucasian and Negro. For this purpose, researcher took 447 sample images of FERET database, out of which 357 images were used for training and for 90 testing. Result of artificial neural network is 82.4% and result of convolution neural network is 98.6%. For the past few decades facial examination has been immensely popular topic to be researched. Face of a person provides demographic information but problem exist when face is in veil, information is not clear to recognize age and gender therefore also yield wrong result. This application are also used in security check point and image search query. Two techniques are used first one is ANN and CNN. Different step is followed to carry out some experiment. Using geometric feature calculation by ANN cascade classifiers cascade classifiers like Nasal, and facial qualities are identified. Then find the distance between them .while comparing outcome between ANN and CNN it can be summarized that final result of CNN method is far better than ANN (Greco, Percannella, Vento, & Vigilante, 2020).

In order to judge the effectiveness of characteristics perceiving from Deep learning perspective. Need for this research is to authenticate information confidently, homeland security and computer security. For this support vector machine (SVM) is used because it merges plans was also suggested for racial and sex perceptron by joining authentic picture. Human face contains large amount of information in soft form for classification of age, ethnicity and gender. Facial nation perceptron is a unique quality. It has two major steps characteristics origin and systematic arranging. there are many approaches are suggested local binary pattern (LBP) and Gobar filter response, apply some feature selection or transformation (W. Wang, He, & Zhao, 2016). For classification use some classifier that is k-nearest neighbor classifiers (KNN) and support vector machines (SVM) to Classified input facial national identity but particularly for facial ethnicity classification use Deep convolutional neural network (DCNN) for the solution of huge magnitude classification. Different classifier are used that is given below.

Table 1: Classifiers used for facial-based person recognition

Classifier	Year	Method	Datasets	Accuracy %
KNN	2018	STASM, Three “T” region MRMR Algorithm	Dalian Minzu University	90
CNN	2018	Geometric Feature	FERET	98.6
ANN	2018	Geometric Feature Calculation	FERET	82.4
CNN	2019	K-PCA K-LDA	Nigeria (Fingerprints)	93.97, 97.26
SVM	2019	LBP, LR, NB, RF, Decision Tree	CAS-PEAL, FERET	99.99
SVM	2017	LBP Gabor	FERET, CAS-PEAL, CVL CFD	99.66
DCNN	2016	LBP, Gabor	MORPHI-II CASIA-PEAL CASIA-Web Face	98.06
DCNN	2016	Growth Curve Model	Millennium Cohort Study	98.06
CNN	2017	CNN	WEAFD	98.4
DCE	2017	Supervised Model	ND-Iris-0405 Multi-Ethnicity Iris	98.02

HMMs	2009	Decision Tree	Local	90.4
CNN	2018	Hybrid SDL	Chinese, Indian	95.02
SVM, KNN	2018	SDM	MORPHI-II, FERET	83.48, 82.30
AMM	2016	LBP, Gabor	FG-NET, Cohn-Kanade, PAL	95.33
PCA	2016	Histogram Equalization Hough Transform techniques	IRIS, Asia1, Asia2	90.33
ANN	2019	Back Propagation, GSO, PSO	Non-Caucasian, Caucasian	95.6, 98.42, 98.25
MTCNN	2018	Joint and Separated, Fully Connected Layer, Bias Estimation	UTK Face	95.01

Ethnicity classification problem has been addressed. Authors, used two datasets, i.e., for the research and experiments (Saliha, Ali, & Rachid, 2019). They used local binary pattern (LBP) to identify the racial characteristics. They used logistic regression (LR) on Spark framework in parallel to large scale datasets. They used Hadoop distributed file system (HDFS) format to memorize the images and Resilient distributed datasets (RDD) in training execution. They used Apache framework and its machine learning library (MLib) is utilized and enforce to deploy the racial category. Different proposed methods, i.e., Naive Bayes (NB), Random Forests (RF), Decision Trees (TR), and Linear SVM are used for race classification. The authors have evaluated above proposed method with respect to processing time.

Table 2 State of the Art Studies

Sr. No	Authors, Year	The Proposed Methodology	Dataset Used	Classification of	Evaluation measures
1.	Mezzoudj Saliha et al. [1], 2019	Integrating LBP and RL	CAS-PEAL and Color FERET	Ethnicity using images	Accuracy= 99.75%
2.	Mezzoudj Saliha et al.[2] 2019	LBP, LR NB, RF, DT, Linear SVM Apache Framework	CAS-PEAL and Color FERET	Ethnicity classification	Accuracy =98% and processing time
3.	Sarfaraz Masood [3], 2019	ANN, LDA, SVM	FERET and MORPHII	Ethnicity using images	Accuracy= 98.6%
4.	H. O. Aworinde et al.[4], 2019	Deep learning, K-LDA, K-PCA	right fingerprint Images of Yoruba, Igbo, and Middle-Belters in Nigeria.	Ethnicity using fingerprints	K-PCA accuracy=94% K-LDA accuracy=97%
5.	Nisha Srinivas et al.[5], 2018	CNN	WEAFD	Age, Gender Fine-Grained Ethnicity	Accuracy=98%
6.	Cunrui Wang et al.[6], 2018	STASM, mRMR, KNN "T" decision	facial images of different ethnic groups	Ethnicity using images	Precision=0.81 Accuracy=0.90

			students on campus at Dalian Minzu University		
7.	Choon-Boon Ng et al.[7]	Svm, LBP	FERET, CAS-PEAL	Gender classification	Accuracy =98%
8.	Muhammad Sajid et al.[8],2018	Neural network, Svm, Knn	MORPH FERET	Gender Ethnicity	Accuracy=81.59%
9.	Zhao Heng et al.[9],2018	CNN, SVM	FERET	Ethnicity	Accuracy =95.2%
10.	Maneet singh et al.[10],2017	Proposed Deep Class-Encoder RDF, NNet	ND-Iris-0405 Multi-Ethnicity Iris CASIA-Iris	Gender Ethinicity	Accuracy RDF=97.22% NNet=97.38%
11.	Inzamam Anwar et al.[11], 2017	CNN, SVM, VGG	MR2, UT, MSDFE, CUFC, JEEFE, Aberden, FERET, CVL, CFD, CASPEALR1	Ethnicity	Accuracy Asian =98.28% Black=99.66% White=99.05%
12	Wei Wang et al.[12], 2016	DCNN, KFCA	CASIA-PEAL CASIA-WebFace MORPH-II, FERET	Facial ethnicity classification	Accuracy Black =100 % White=99.4 %

For features reduction, Elastic Bunch Graph Matching (EBGM), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) have been used. When SVM has been used as a classifier, it achieved accuracy up to 98 %. Multi-layer Perceptron (MLP) and SVM are used for Asian and Non-Asian people respectively. Author have also proposed their own model by integrating LBP and RL classifiers. However, it can work on limited datasets.

Human face provides wealth of information that are used for race, age, gender and ethnicity classification. Ethnicity remains constant during whole life and give help for face recognition system. In this paper just classified the Asian and Non-Asian people with extraction of some demographic feature (Anwar & Islam, 2017). In this paper, for ethnicity classification different method are proposed i.e. convolutional neural network (CNN) that is being utilized the segregation the images using layer like rectified linear and convolutional layer to identify the object attributes. Using 200*200 input size the neuron will 4k that is over fitting reducing size with 32*32 =1024 weights. That is fit for first hidden layer. Second method is used Support vector machines (SVM) for segregate the feature contained in the image. Local binary pattern (LBP) and Gobar are used for contrast feature.

3.0 Proposed Methodology

3.1 Introduction

To avoid the complex feature extraction problem, we introduce a new methodology for facial expression recognition that generate the faster results using convolution neural networks. For this purpose, the images of characters are normalized and features are extracted using Gabor feature extraction. Facial Expression Research Group Database (FERG-DB) is used as dataset that contains 55767 annotated face images of six stylized characters.

3.1.1 Collection for Analysis and of Relevant Data

This learning is succeeding mutually graphic and investigational learning. Associated facts determination is collected from concluded records, articles, research paper, thesis magazine and from internet source. For analysis materials, all the study is settled and composed. To reach at particular final arguments the materials and subjects is discussed with the instructor for comfort.

3.1.2 Identification of the Problem

As in problem statement we discussed that, can convolutional neural network be helpful in facial expression recognition or not. Problem statement has recognized to bargain the explanation will be in the succeeding period. The well and well-organized results have acquired from this suggested work. The results are obtained by using MATLAB toolbox and Gabor feature extraction is used for extracting features from images.

3.1.3 Research Technique

This technique depends on the literature-based learning. It means ideally investigation of that methodology which contains arguments and selection of theoretical materials and imaginative materials and these theories give a complete evaluation in the context, by proposing perfect solution try to decide and finding main issues. This study motivate will be in empirically.

3.1.4 Used Datasets

The relevant data which is used and collected from internet source (books, topic, article, research paper and thesis). Globally available dataset is used in this research named as

- Jaffe database
- Senthil database
- KDEF dataset
- UTKFace
- Faces
- FERG database
- some other facial images

All of these datasets are combined and grouped into seven basic expressions, which contain images of different expressions like happy, sad, surprised, neutral, fear, disgust and angry.

3.1.5 Technique for Data Analysis Procedure

The collected data was checked and extracted by different features. A specific method or procedure used to classify images. The method that is used to classify images of the proposed model is convolutional neural network. Convolutional Neural Networks are often normal "two hidden layers that use a lot of managed or predicted classification. Deep learning design neural networks are different from convolutional neural networks "normal" because of the extra hidden layers as shown in figure 3.1. Neural network calculation is perfect using deep learning after the nature of the human brain. According to the human mind, the Convolutional neural networks (CNN) is also the basics of editing (neuron). Processing is divided into groups called classes. CNN consists of three layers, which are the input and output layer and the hidden layers. When images develop before and give input with Convolutional neural networks (CNN) the output image format trend indicators in the form of slashes, one for each purpose. The class with the highest score we refer to the category that is most likely to be targeted in the picture. Convolutional neural networks (CNN) training aims to monitor the weights that make full use of the scores right category and to lose masses of untrue accusation. During the training of neural networks, is measure the degree gap between the corrected results is called lose and calculated results are losing, the goal is a hidden layer of normal loss of losing more than a wide range of training as shown in figure 3.1.

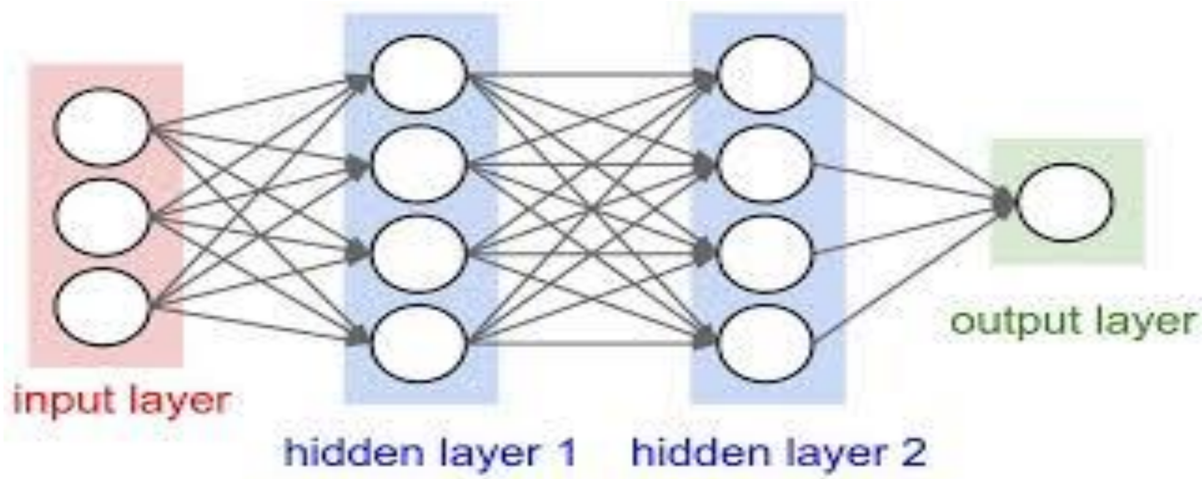

Figure 1 Convolutional Neural Networks

Convolutional learning not just the opposite of "normal" NN (neural networks) but support vector machine (SVM), which is more common and the sorting algorithm because this can train with the style of uncensored or uncensored mutual supervision and supervision functions of learning. Separation of gray scale will be used for further processing to perfect images and make them into classification systems and improved results. It will break the image into pixels on a confidential basis and to calculate the rows and columns, that allow the algorithm.

3.1.6 Analysis Tool (Software)

MATLAB tool is used for investigation and analysis process. For calculation of math works MATLAB tool can be used to evaluate and checked the competence of the suggested model and algorithms (Durán, Gallardo, Toral, Martínez-Torres, & Barrero, 2007). To design and analyze the system MATLAB is used. MATLAB is used for the digital image procession, machine learning, control design, computer vision, communication and signal processing etc. Classification performance is analyzed from MATLAB. The plotting of data and function, implementations of algorithms, matrix manipulations and interface with various programming language MATLAB allows.

3.1.7 Computation Accuracy

The algorithm of performance can be evaluated in terms of specificity, accuracy and sensitivity. Matrix violation definitions TP (true positive), TN (true negative), FN (false negative), FP(false positive) and planned the expected result and true results to calculate the accuracy and sensitivity and specificity of ground truth are displayed in figure 3.2.

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Expected out comes	Ground truth		
	Positive	Negative	Row total
Positive	TP	FP	TP+FP
Negative	FN	TN	FN+TN
Column total	TP+FN	FP+TN	TP+FP+FN+TN

Figure 2 Confusion matrix defining the term TN, FP, FN, and TN

Where n is the number of true positives, used to indicate the total number of abnormalities that are classified correctly, TN is no real negatives, used to refer to normal cases classified correctly is a false positive and is used to indicate abnormalities correct or confidential, when it is actually normal cases and the number of false negatives is the national front, is used to refer to normal confidentiality or detection error, when in fact anomalies, every one of these results parameters are calculated using the total number of sample for detection of expression.

3.1.8 Limitation of this Research

Following limitation of this research are given below

- The material which is used in this research from previous research was among the duration of 2015 to 2019 (last four years).
- For experiment, the dataset used has limited number of images.
- Through MATLAB analysis tool this proposed model has justified.
- Front face and rich detail images are required for training.
- Luminance has major factor on accuracy.
- Side poses cause decrease in accuracy results.
- Large number of images are required for training and testing purpose.

3.2 Methods and Materials

3.2.1 Image Preprocessing and Data Acquisition

Gabor feature extraction is used for image preprocessing, images are converted into .png format and every image have the same dimension 512 x 512. All of the dataset images are converted into same dimension by separating different channels these channels are green, blue, red and intensity. Every image with single channel is separated and treated as a new single image with a single channel.

3.2.2 Images Segmentation by CNN for Multi-Modality

Deep learning procedure is a type of machine that may lean and grade of feature extraction by the structure of high–level to low-level ones. Deep models is a type of the convolutional neural networks (CNN) (Yushkevich et al., 2006), in which trainable lattice and resident area merging procedures stay useful alternate input images on the rare, subsequent in the grading of gradually composite sorts. Single stuff of convolutional neural network (CNN) is its competency near detention extremely non –linear comparing among outputs and inputs. When accomplished with suitable regularization, convolutional neural networks (CNN) can succeed in the greater presentation on pictorial object appreciation and image classification jobs. In accumulation, convolutional neural networks (CNN) has also been used in insufficient other submissions. In (Jain & Seung, 2009) and (Helmstaedter et al., 2013) the volumetric electron microscopy images have segmented and bring back from functional convolutional neural networks (CNN). Functional deep CNN to distinguish histology mitosis of images by using classifier pixel patches are established (Giusti, Cireşan, Masci, Gambardella, & Schmidhuber, 2013).

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While CNN has used to work in previous revisions, none of them had focused on inclusion and integration of multi-modality method of image data.

CNN only allow in multiple entry maps similar to different methods of data, which provides common formalities to incorporate multiple data method.

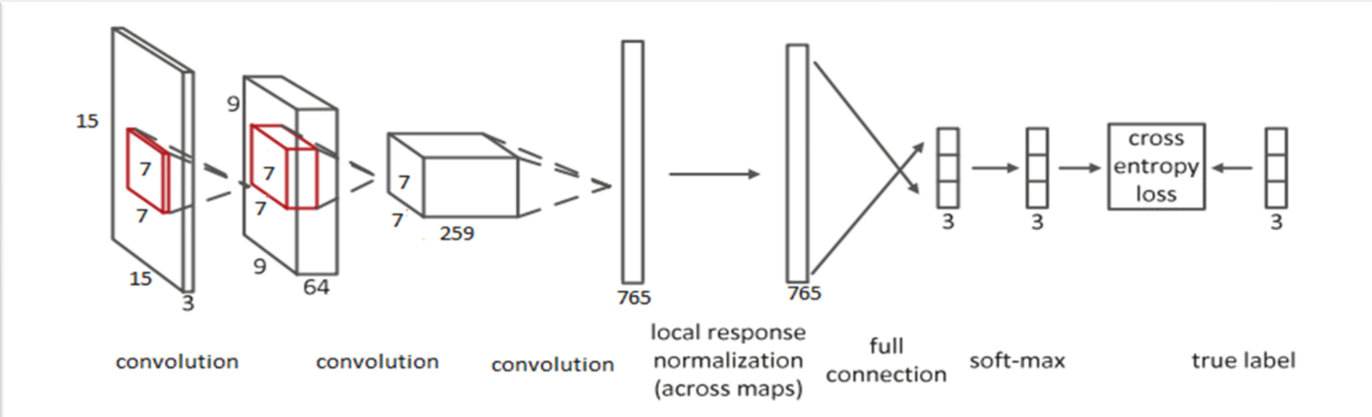


Figure 3 Patch size 15x15 is taken as input and its detailed structural design of the convolutional neural networks are obtained.

3.2.3 Deep Convolutional Neural Networks (CNN) Structural Design

In that proposed study, four convolutional neural networks (CNN) structural design has established on multi-modality for segmentation of images. In the following, the CNN structural design provides detailed and to explain the system which is used in this work having the input patch size 15x15. The complete structural design has shown in Fig. 3.3. That convolutional neural networks (CNN) construction confined in three different feature maps which correspond images patches of 15x15. Then that's useful for three convolutional sheets and one sheet is fully associated. These networks too useful to softmax sheets and local reaction normalization.

First only 64 convolutional class characteristic plots. Both feature pieces associated with all three have plots more than 7 x 7 size filters. We used a single pixel stride size. This will create the maps feature size 9 x 9 in this layer. This layer generates first division convolution output as inputs and only 259 feature pieces. Second layer had associated attribute maps all maps feature in previous class made a size7 filters x 7. Again, we use a pixel size pride. The third layer convolution 765 feature limited pieces 1 x 1. For all maps feature the previous layer of 7 x 7 filters. We also used a pixel pitch size in this layer. In all of the repaired linear unit, the convolutional sheet has useful in the proposed convolutional procedure (Nair & Hinton, 2010). The use of ReLU layer may accelerate the training of CNN that has been exposed. Apart from the documents convolutional, used certain types of extra paper at CNN. Specifically, the structure of normalization limited answer helpful after the third paper cut impose contrasts between identical spatial position through various feature. Successfully inserted layer 3 normalization may outputs relating to three categories. Softmax 3-way paper used to create spread over 3 class Abel export later fully connected. Our network dropped damage divided between entropy prediction and brand truth crushed. Now adding, recycled failure to more learn vigorous types(Hinton, Srivastava, Krizhevsky, Sutskever, & Salakhutdinov, 2012) and overfitting is decreased. This action put the production each neuron to zero with the possibility of 0.5, waster was useful earlier papers in relation to full geometry in fig. 3.2 CNN. In whole, that's trained limitations to amount on this structure 5.332.995.

Also, the other three deliberated CNN planning with input patch design sizes 9 x 9 and 17 x 17 and 22 x 22. These CNN planning of convolution consists of convolutional sheet and change of feature strategies (S. WANG et al., 2020). Organization and local reactions softmax separately have practically in the structural design of the paper. We also pool mattress Max structural design with correct details size 22 x 22 after convolutional first sheet. Said size is set to 2 x 2 and 2 x 2 used for pooling size. Provided full information on these structural design in table 3.1. In this table with different input patches size are explain of the CNN structural design in this effort. Full.com, Norm. and Conv. denotes fully- connected, normalization and convolutional layers respectively.

Table 0 CNN Structural Design

Patch size	Layer type	Layer1	Layer2	Layer3	Layer4	Layer5	Layer6	Layer 7
9x9	Layer type #of feat. Map Filter size Conv. stride Input size	Conv. 259 7x7 1x1 9x9	Conv. 1024 7x7 1x1 7x7	Norm. 1024 _ _ 1x1	Full.com 3 1x1 1x1 1x1	Softmax 3 _ _ 1x1	_ _ _ _ _	_ _ _ _ _
15x15	Layer type #of feat. Map Filter size Conv. stride Input size	Conv. 64 7x7 1x1 15x15	Conv. 259 7x7 1x1 9x9	Conv. 765 7x7 1x1 7x7	Norm 765 _ _ 1x1	Full.com 3 1x1 1x1 1x1	Softmax 3 _ _ 1x1	_ _ _ _ _
17x17	Layer type #of feat. Map Filter size Conv. stride Input size	Conv. 64 7x7 1x1 17x17	Conv. 128 7x7 1x1 15x15	Conv. 256 7x7 1x1 9x9	Conv. 765 7x7 1x1 7x7	Norm. 765 _ _ 1x1	Full.com 3 1x1 1x1 1x1	Soft max 3 _ _ 1x1
22x22	Layer type #of feat. Map Filter size Pooling stride Pooling size Input size	Conv. 64 7x7 - _ 22x22	Pooling 64 _ 2x2 2x2 18x18	Conv. 259 7x7 _ _ 9x9	Conv. 765 7x7 _ _ 7x7	Norm. 765 _ _ _ 1x1	Full.com 3 1x1 _ _ 1x1	Soft max 3 _ _ _ 1x1

3.2.4 Calibration and Model Training

This method creates duplicates over 10,000, all three points that correspond to each topic. We used a single authorization method-topic-rage at the expense of performance. In detail, we used seven of the eight subjects of the training system and the rest used are subject to an assessment of performance. Description of normal cross folding. All the patches of each exercise in a single file, set stored in to the files altogether. We have used seven expressions in these spots for the entrance of CNN repeatedly to keep fit. Note that the patches in each group of files in arbitrary operation command used.

Masses in networks that arbitrarily was with Gaussian distribution N (0.1 × 10-4). Through training, and serious internal rationalized random gradient associated with 0.9 and enhance the overall degradation of 4 x 10-4. Favoritisms has changed to convolutional full document in 1. The quantity was changed to justify periods set containing patches for a particular article arbitrarily in a group setting. And the learning rate was set at 4 x 10-4 at first.

Succeeding, justification set first me to attain granular estimate to the optimum period using decreasing the endorsement error. The period used for the classic sequence for education and to justify the teams consist of seven people. Then was condensed learning extent attribute of 10 twice continuously, the classic was eligible for about 10 intervals each time. Following this method, the net with the correction of volume 15 x 15 approx. 370 times. The practice gained in less than one day in the attractive K20c Tesla "with 2496. The structures have been completed with an additional patch size and related technology. One of the advantages of using CNN for the picture is, at the time of the test, the entire image can be used as input for the network to create a plot to secede, and to predict the level of unwanted (Giusti et al., 2013).This clues to very proficient separation at assessment stage. For example, this convolutional neural networks (CNN) representations acquired almost 50 to 100s for segmentation to the images size 259 x 259.

This chapter describes the research plan for the successful completion of this study. The graph shows all visible part in the early stages. In accordance with this chapter after searching the plane we can describe the research methods and study these descriptions details about dataset used in the experiment explains in detail. Further explain the procedure of technique which will used in the data set. After explaining the procedure of technique, we express around analysis tool (MATLAB software) which has backbone use for implementation.

3.3 Data set

The dataset used for the research and experiment purpose has been collected from different online sources. The relevant data which is used and collected from internet source (books, topic, article, research paper and thesis). Globally available dataset is used in this research named as Jaffe database, Senthil database, KDEF dataset, UTKFace, Faces, FERG database and some other facial images all of these datasets are combined and grouped into seven basic expressions, which contain images of different expressions like happy, sad, surprised, neutral, fear, disgust and angry. We used 60% of the data for training purpose, 20% of the data for cross validation and 20% of the data for testing of the proposed system.

Table 4 Dataset details used for research and experiments

Sr. No	Data set	Main features	Capacity	Expression	Environment
1.	CK+ (K. Li, Jin, Akram, Han, & Chen, 2019)	The most common lab-controlled dataset	10,708 images and 327 video sequences collected	7	Scientific research
2.	CAS(ME)2 (K. Li et al., 2019)	Both spontaneous micro and macro-expressions	87 images of micro and macro expressions 57 micro-expressions	4	Scientific research
3.	AFEW 4.0 (Samadiani et al., 2019)	Videos from real world scenarios	1268 videos	7	Real
4.	MMI (Samadiani et al., 2019)	Dual view in an image	1520 videos of Posed expression	6	Scientific research
5.	SFEW (Samadiani et al., 2019)	Images from real world scenarios	700 images	7	Real
6.	CMU Multi-PIE(Samadiani et al., 2019)	Simulation of 19 various lighting conditions	755,370 images	6	Scientific research

7.	AM-FED (Samadiani et al., 2019)	Webcam videos from online viewers	242 videos spontaneous expression	Smile	Real
8.	JAFEE(Z. Zhang, Luo, Loy, & Tang, 2018)	Evaluate the facial expression	213 images	7	Scientific research
9.	CAS-PEAL(Samadiani et al., 2019)	Simulation of various backgrounds in the lab	Images of posed expression	5	Scientific research
10.	UTSC-NVIE (target-focused) (Samadiani et al., 2019)	The biggest thermal-infrared dataset	Videos of posed and spontaneous expression	6	Scientific research
11.	SPOS (target-focused)(Samadiani et al., 2019)	Subjects with different accessories	231 images of spontaneous, and posed expression	6	Scientific research
12.	VAMGS (non-visual) (Samadiani et al., 2019)	Visual-audio real world dataset	1867 images of spontaneous expression 1018 emotional voices	6	Real
13.	MMSE (Samadiani et al., 2019)	A multimodal dataset	10 GB data per subject	10	Scientific research
14.	OULU-CASIA (Z. Zhang et al., 2018)	Evaluate face features	480 images	6	Scientific research
15.	BU-3DFE (Makhmudkhujaev, Abdullah-Al-Wadud, Iqbal, Ryu, & Chae, 2019)	Face identification and detection	606 images	6	Scientific research
16.	RAFD(Wu & Lin, 2018)	The most common lab-controlled dataset	High quality of database face	8	Scientific research

3.3.1 Preprocessing

Preprocessing of images is done; we convert images into .png extension and set the size 512 x 512 for each image. The preprocessing step also involve the separation of Red, Green, Blue and intensity channel filtration that help to convert each expression and increase the efficiency. Gabor Feature extraction technique is used for this purpose.

3.3.2 Segmentation

For segmentation of images, in this research work, Fuzzy C mean algorithm has been used. The working fuzzy C mean algorithm has been described has under;

Fuzzy C mean is a data clustering method in which a data set is assembled into N clusters. In which each data point in the data set fitting to every cluster to a definite degree. Data point near to the center of a cluster have a high degree of connection and data point far from center of cluster have low degree of connection

$$\sum_{j=1}^{k}\sum_{x_i \in c_j} ui^m j(xi - \mu j)^2$$

Where,

- μij is the degree to which an observation xi belongs to a cluster *cj*
- μj is the center of the cluster *j*
- $\mu ij$is the degree to which an observation xi belongs to a cluster *cj*
- *m* is the fuzzifier

3.4 Classification of Facial Expression using Convolutional Neural network

Convolutional network is deep learning algorithm. It takes an input image allocate priority to different images and compare it with other.

3.4.1 Convolutional Layer

The essential preprocessing is lesser as associated with another algorithm. Convolutional layer consists of set of constraints. Throughout the forward pass we slide every filter transversely to the height and width of input volume. When we slide the filter ended to the width and height then it produces 2-dimensional activation map.

3.4.2 Pooling Layer

It is common to add pooling layer in convolutional network. The pooling layer autonomously on every input depth slice. The most found is pooling with filter of 2x2 that is pragmatic with 2 down sample each depth slice input by 2 sideways both height and width and remove 75 % of the activation.

More generally, the pooling layer:

- Accepts a volume of size Width1×Height1×Dim1Width1×Height1×Dim1
- Requires two hyper parameters:
  - their spatial extent FF,
  - the stride SS,
- Produces a volume of size Width2×Height2×Dim2Width2×Height2×Dim2 where:
  - Width2=(Width1−F)/Str+1Width2=(Width1−F)/S+1
  - Height2=(Height1−F)/Str+1Height2=(Height1−F)/Str+1
  - Dim2=Dim1Dim2=Dim1
- It Introduces zero parameters later it calculates a fixed function of the input
- For Pooling layers, it is not common to pad the input using zero-padding.

3.4.3 Normalization Layer

Several type of normalization layers have been projected in CNN.

3.4.4 Fully Connected Layer

Neuron in an abundantly connected layer have full connection with previous layer. Their activation can be calculated with matrix by a bias offset.

Detail of experiments

To ensure the robustness of the proposed method, experiments have been performed on each of the red, green, blue, intensity and colour channels of the dataset. The detail of the experiments is shown in Table 1.

Table 5: detail of the experiments performed on each of the red, green, blue, intensity and colour channels of the dataset.

Experiment#	Channel Explored	Classes	No. samples per cl
Exp. No. 01	Red Channel	Bengali, Indian	Bengali = 583, Indian = 468
Exp. No. 02	Red Channel	Bengali, Pakistani	Bengali = 583, Pakistani = 6
Exp. No. 03	Red Channel	Bengali, Chinese	Bengali = 583, Chinese = 74
Exp. No. 04	Red Channel	Bengali, Gilgit	Bengali = 583, Gilgit = 10
Exp. No. 05	Green Channel	Bengali, Indian	Bengali = 583, Indian = 468
Exp. No. 06	Green Channel	Bengali, Pakistani	Bengali = 583, Pakistani = 6
Exp. No. 07	Green Channel	Bengali, Chinese	Bengali = 583, Chinese = 74
Exp. No. 08	Green Channel	Bengali, Gilgit	Bengali = 583, Gilgit = 10
Exp. No. 09	Blue Channel	Bengali, Indian	Bengali = 583, Indian = 468

Blue Channel	Bengali, Pakistani	Bengali = 583, Pakistani = 698
Blue Channel	Bengali, Chinese	Bengali = 583, Chinese = 747
Blue Channel	Bengali, Gilgit	Bengali = 583, Gilgit = 10
Intensity Channel	Bengali, Indian	Bengali = 583, Indian = 468
Intensity Channel	Bengali, Pakistani	Bengali = 583, Pakistani = 698
Intensity Channel	Bengali, Chinese	Bengali = 583, Chinese = 747
Intensity Channel	Bengali, Gilgit	Bengali = 583, Gilgit = 10
RGB-Color	Bengali, Indian	Bengali = 583, Indian = 468
RGB-Color	Bengali, Pakistani	Bengali = 583, Pakistani = 698
RGB-Color	Bengali, Chinese	Bengali = 583, Chinese = 747
RGB-Color	Bengali, Gilgit	Bengali = 583, Gilgit = 10
Red Channel	Bengali, Indian, Pakistani	Bengali=583,Indian=468,Pakistani=698
Red Channel	Bengali, Indian, Chinese	Bengali=583,Indian=468,Chinese=747
Red Channel	Bengali, Indian, Gilgit	Bengali=583, Indian=468,Gilgit=10
Red Channel	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,Chinese=747
Red Channel	Bengali, Pakistani, Gilgit	Bengali=583,Pakistani=698,Gilgit=10
Red Channel	Bengali, Chinese, Gilgit	Bengali=583,Chinese=747,Gilgit=10
Red Channel	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,Chinese= 747
Red Channel	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 698,Gilgit = 10
Red Channel	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747,Gilgit = 10
Red Channel	Pakistani, Chinese, Gilgit	Pakistani=698,Chinese=747,Gilgit= 10
Green Channel	Bengali, Indian, Pakistani	Bengali=583,Indian=468,Pakistani = 698
Green Channel	Bengali, Indian, Chinese	Bengali = 583,Indian = 468,Chinese=747
Green Channel	Bengali, Indian, Gilgit	Bengali = 583,Indian = 468,Gilgit = 10
Green Channel	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,Chinese=747
Green Channel	Bengali, Pakistani, Gilgit	Bengali= 583,Pakistani = 698,Gilgit = 10
Green Channel	Bengali, Chinese, Gilgit	Bengali = 583,Chinese = 747,Gilgit = 10
Green Channel	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,Chinese = 747
Green Channel	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 698,Gilgit = 10
Green Channel	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747,Gilgit = 10
Green Channel	Pakistani, Chinese, Gilgit	Pakistani=698,Chinese=747,Gilgit = 10
Blue channel	Bengali, Indian, Pakistani	Bengali=583,Indian=468,Pakistani = 698

Exp. No. 42	Blue channel	Bengali, Indian, Chinese	Bengali =583,Indian= 468,C 747
Exp. No. 43	Blue channel	Bengali, Indian, Gilgit	Bengali = 583,Indian =468,G
Exp. No. 44	Blue channel	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,C
Exp. No. 45	Blue channel	Bengali, Pakistani, Gilgit	Bengali=583,Pakistani=698,
Exp. No. 46	Blue channel	Bengali, Chinese, Gilgit	Bengali = 583,Chinese = 747
Exp. No. 47	Blue channel	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,C 747
Exp. No. 48	Blue channel	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 698
Exp. No. 49	Blue channel	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747
Exp. No. 50	Blue channel	Pakistani, Chinese, Gilgit	Pakistani =698,Chinese = 74 10
Exp. No. 51	Blue channel	Bengali, Indian, Pakistani	Bengali=583,Indian=468,Pa
Exp. No. 52	Blue channel	Bengali, Indian, Chinese	Bengali=583,Indian = 468,C 747
Exp. No. 53	Blue channel	Bengali, Indian, Gilgit	Bengali = 583,Indian = 468,
Exp. No. 54	Blue channel	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,
Exp. No. 55	Blue channel	Bengali, Pakistani, Gilgit	Bengali= 583,Pakistani = 698
Exp. No. 56	Blue channel	Bengali, Chinese, Gilgit	Bengali = 583,Chinese = 747
Exp. No. 57	Blue channel	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,C 747
Exp. No. 58	Blue channel	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 698
Exp. No. 59	Blue channel	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747
Exp. No. 60	Blue channel	Pakistani, Chinese, Gilgit	Pakistani= 698,Chinese = 74 10
Exp. No. 61	Intensity Channel	Bengali, Indian, Pakistani	Bengali=583,Indian= 468,Pa
Exp. No. 62	Intensity Channel	Bengali, Indian, Chinese	Bengali=583,Indian = 468,C 747
Exp. No. 63	Intensity Channel	Bengali, Indian, Gilgit	Bengali = 583,Indian = 468,
Exp. No. 64	Intensity Channel	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,
Exp. No. 65	Intensity Channel	Bengali, Pakistani, Gilgit	Bengali= 583,Pakistani = 698
Exp. No. 66	Intensity Channel	Bengali, Chinese, Gilgit	Bengali = 583,Chinese = 747
Exp. No. 67	Intensity Channel	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,C 747
Exp. No. 68	Intensity Channel	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 698
Exp. No. 69	Intensity Channel	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747
Exp. No. 70	Intensity Channel	Pakistani, Chinese, Gilgit	Pakistani= 698,Chinese = 74 10
Exp. No. 71	Intensity Channel	Bengali, Indian, Pakistani	Bengali=583,Indian=468,Pa

Intensity Channel	Bengali, Indian, Chinese	Bengali=583,Indian=468,Chinese = 747
Intensity Channel	Bengali, Indian, Gilgit	Bengali = 583,Indian = 468,Gilgit = 10
Intensity Channel	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,Chinese=747
Intensity Channel	Bengali, Pakistani, Gilgit	Bengali = 583,Pakistani = 698,Gilgit = 10
Intensity Channel	Bengali, Chinese, Gilgit	Bengali = 583,Chinese = 747,Gilgit = 10
Intensity Channel	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,Chinese = 747
Intensity Channel	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 698,Gilgit = 10
Intensity Channel	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747,Gilgit = 10
Intensity Channel	Pakistani, Chinese, Gilgit	Pakistani= 698,Chinese = 747,Gilgit = 10
RGB-Color	Bengali, Indian, Pakistani	Bengali=583,Indian=468,Pakistani = 698
RGB-Color	Bengali, Indian, Chinese	Bengali=583,Indian = 468,Chinese = 747
RGB-Color	Bengali, Indian, Gilgit	Bengali = 583,Indian = 468,Gilgit = 10
RGB-Color	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,Chinese=747
RGB-Color	Bengali, Pakistani, Gilgit	Bengali= 583,Pakistani = 698,Gilgit = 10
RGB-Color	Bengali, Chinese, Gilgit	Bengali = 583,Chinese = 747,Gilgit = 10
RGB-Color	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,Chinese = 747
RGB-Color	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 698,Gilgit = 10
RGB-Color	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747,Gilgit = 10
RGB-Color	Pakistani, Chinese, Gilgit	Pakistani= 698,Chinese = 747,Gilgit = 10
RGB-Color	Bengali, Indian, Pakistani	Bengali=583,Indian=468,Pakistani = 698
RGB-Color	Bengali, Indian, Chinese	Bengali=583,Indian=468,Chinese = 747
RGB-Color	Bengali, Indian, Gilgit	Bengali = 583,Indian = 468,Gilgit = 10
RGB-Color	Bengali, Pakistani, Chinese	Bengali=583,Pakistani=698,Chinese=747
RGB-Color	Bengali, Pakistani, Gilgit	Bengali= 583,Pakistani = 698,Gilgit = 10

Exp. No. 96	RGB-Color	Bengali, Chinese, Gilgit	Bengali = 583,Chinese = 747
Exp. No. 97	RGB-Color	Indian, Pakistani, Chinese	Indian=468,Pakistani=698,C 747
Exp. No. 98	RGB-Color	Indian, Pakistani, Gilgit	Indian = 468,Pakistani = 69
Exp. No. 99	RGB-Color	Indian, Chinese, Gilgit	Indian = 468,Chinese = 747
Exp. No. 100	RGB-Color	Pakistani, Chinese, Gilgit	Pakistani=698,Chinese = 74
Exp. No. 101	Red channel	Bengali, Indian, Chinese, Pakistani	Bengali = 583,Indian = 468, 747,Pakistani = 698
Exp. No. 102	Red channel	Bengali, Indian, Chinese, Gilgit	Bengali = 583,Indian = 468, 747,Gilgit = 10
Exp. No. 103	Green channel	Bengali, Indian, Chinese, Pakistani	Bengali = 583,Indian = 468, 747,Pakistani = 698
Exp. No. 104	Green channel	Bengali, Indian, Chinese, Gilgit	Bengali = 583,Indian = 468, 747,Gilgit = 10
Exp. No. 105	Blue channel	Bengali, Indian, Chinese, Pakistani	Bengali = 583,Indian = 468, 747,Pakistani = 698
Exp. No. 106	Blue channel	Bengali, Indian, Chinese, Gilgit	Bengali = 583,Indian = 468, 747,Gilgit = 10
Exp. No. 107	Intensity channel	Bengali, Indian, Chinese, Pakistani	Bengali = 583,Indian = 468, 747,Pakistani = 698
Exp. No. 108	Intensity channel	Bengali, Indian, Chinese, Gilgit	Bengali = 583,Indian = 468, 747,Gilgit = 10
Exp. No. 109	RGB-Color	Bengali, Indian, Chinese, Pakistani	Bengali = 583,Indian = 468, 747,Pakistani = 698
Exp. No. 110	RGB-Color	Bengali, Indian, Chinese, Gilgit	Bengali = 583,Indian = 468, 747,Gilgit = 10
Exp. No. 111	Red channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Bengali = 583,Indian = 468, 698,Chinese = 747,Gilgit =
Exp. No. 112	Green channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Bengali = 583,Indian = 468, 698,Chinese = 747,Gilgit =
Exp. No. 113	Blue channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Bengali = 583,Indian = 468, 698,Chinese = 747,Gilgit =
Exp. No. 114	Intensity channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Bengali = 583,Indian = 468, 698,Chinese = 747,Gilgit =
Exp. No. 115	RGB-Color	Bengali, Indian, Pakistani, Chinese, Gilgit	Bengali = 583,Indian = 468, 698,Chinese = 747,Gilgit =

RESULTS AND DISCUSSION

In this research, the globally available dataset is used (Jaffe database, Senthil database, KDEF dataset, UTKFace, faces, FERG database and some other facial images) which contain images of different expressions like happy, sad, surprised, neutral, fear, disgust and angry. In this research work, we have performed experiments in different ways by shuffling images and generating our own grouped data.

Results of the experiments

Several experiments have been performed on each of the red, green, blue, intensity, and color channel of the dataset under experiments as shown in Table 4.1.

Table 6 Results of the experiments obtained through the proposed model for different experiments on each of the red, green, blue, intensity, and color channel of the dataset under experiments.

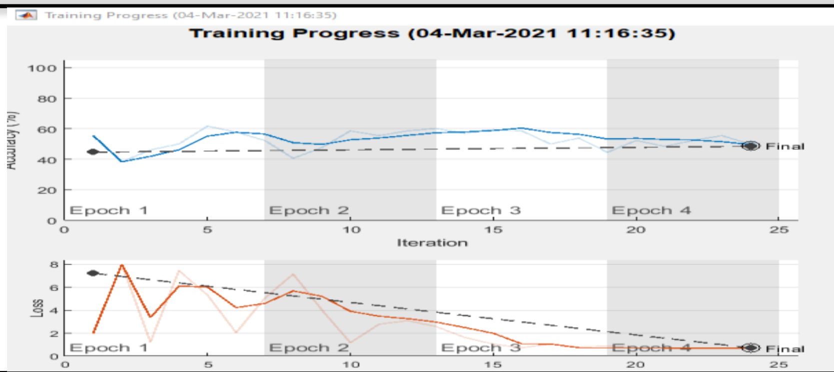
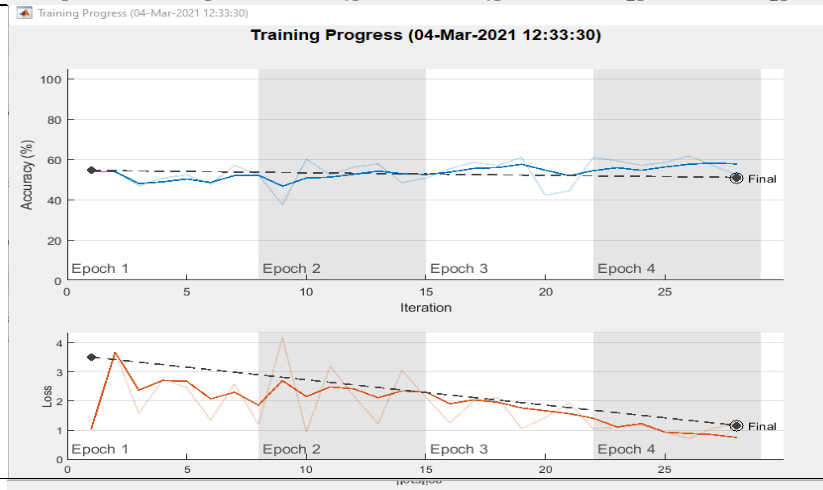
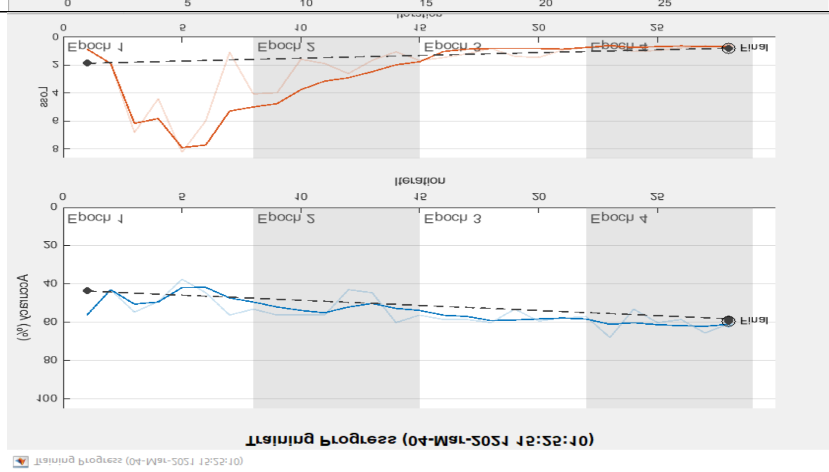
Experiment No.	Channel Explored	Classes	Accuracy achieved
Exp. No. 01	Red Channel	Bengali, Indian	Accuracy = 0.4885
Exp. No. 02	Red Channel	Bengali, Pakistani	Accuracy = 0.5078
Exp. No. 03	Red Channel	Bengali, Chinese	Accuracy = 0.5964
Exp. No. 04	Red Channel	Bengali, Gilgit	Accuracy = 0.9864
Exp. No. 05	Green Channel	Bengali, Indian	Accuracy = 0.5458
Exp. No. 06	Green Channel	Bengali, Pakistani	Accuracy = 0.5204
Exp. No. 07	Green Channel	Bengali, Chinese	Accuracy = 0.6114
Exp. No. 08	Green Channel	Bengali, Gilgit	Accuracy = 0.9864
Exp. No. 09	Blue Channel	Bengali, Indian	Accuracy = 0.5458
Exp. No. 10	Blue Channel	Bengali, Pakistani	Accuracy = 0.5204
Exp. No. 11	Blue Channel	Bengali, Chinese	Accuracy = 0.6054
Exp. No. 12	Blue Channel	Bengali, Gilgit	Accuracy = 0.9864
Exp. No. 13	Intensity Channel	Bengali, Indian	Accuracy = 0.4924
Exp. No. 14	Intensity Channel	Bengali, Pakistani	Accuracy = 0.5361
Exp. No. 15	Intensity Channel	Bengali, Chinese	Accuracy = 0.6054
Exp. No. 16	Intensity Channel	Bengali, Gilgit	Accuracy = 0.9864
Exp. No. 17	RGB-Color	Bengali, Indian	Accuracy = 0.6603
Exp. No. 18	RGB-Color	Bengali, Pakistani	Accuracy = 0.6719
Exp. No. 19	RGB-Color	Bengali, Chinese	Accuracy = 0.8221
Exp. No. 20	RGB-Color	Bengali, Gilgit	Accuracy = 0.9831
Exp. No. 21	Red Channel	Bengali, Indian, Pakistani	Accuracy = 0.4404
Exp. No. 22	Red Channel	Bengali, Indian, Chinese	Accuracy = 0.4421
Exp. No. 23	Red Channel	Bengali, Indian, Gilgit	Accuracy = 0.5606
Exp. No. 24	Red Channel	Bengali, Pakistani, Chinese	Accuracy = 0.4427
Exp. No. 25	Red Channel	Bengali, Pakistani, Gilgit	Accuracy = 0.5265
Exp. No. 26	Red Channel	Bengali, Chinese, Gilgit	Accuracy = 0.6065
Exp. No. 27	Red Channel	Indian, Pakistani, Chinese	Accuracy = 0.5265
Exp. No. 28	Red Channel	Indian, Pakistani, Gilgit	Accuracy = 0.5973
Exp. No. 29	Red Channel	Indian, Chinese, Gilgit	Accuracy = 0.5980
Exp. No. 30	Red Channel	Pakistani, Chinese, Gilgit	Accuracy = 0.5813
Exp. No. 31	Green Channel	Bengali, Indian, Pakistani	Accuracy = 0.4266
Exp. No. 32	Green Channel	Bengali, Indian, Chinese	Accuracy = 0.4232
Exp. No. 33	Green Channel	Bengali, Indian, Gilgit	Accuracy = 0.4962
Exp. No. 34	Green Channel	Bengali, Pakistani, Chinese	Accuracy = 0.4289
Exp. No. 35	Green Channel	Bengali, Pakistani, Gilgit	Accuracy = 0.5452
Exp. No. 36	Green Channel	Bengali, Chinese, Gilgit	Accuracy = 0.6576
Exp. No. 37	Green Channel	Indian, Pakistani, Chinese	Accuracy = 0.6198
Exp. No. 38	Green Channel	Indian, Pakistani, Gilgit	Accuracy = 0.6078
Exp. No. 39	Green Channel	Indian, Chinese, Gilgit	Accuracy = 0.5359
Exp. No. 40	Green Channel	Pakistani, Chinese, Gilgit	Accuracy = 0.6281
Exp. No. 41	Blue channel	Bengali, Indian, Pakistani	Accuracy = 0.3935
Exp. No. 42	Blue channel	Bengali, Indian, Chinese	Accuracy = 0.4200

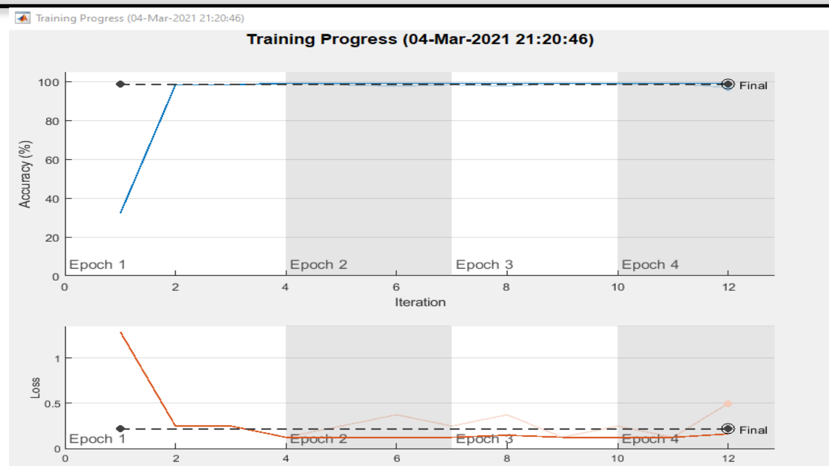
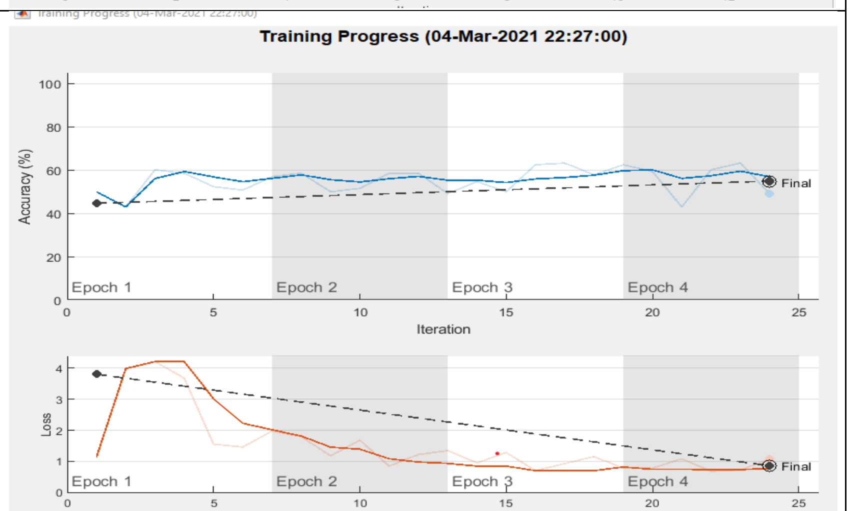
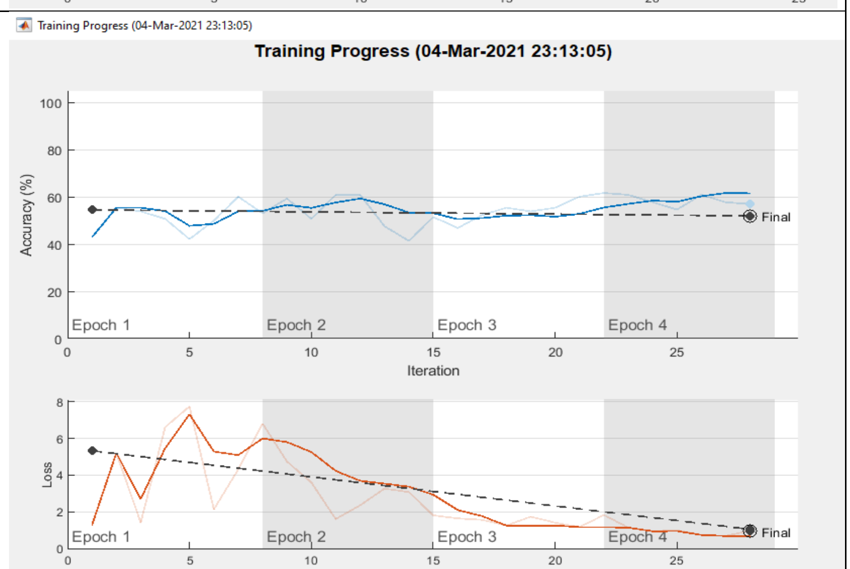
Exp. No. 43	Blue channel	Bengali, Indian, Gilgit	Accuracy = 0.5076
Exp. No. 44	Blue channel	Bengali, Pakistani, Chinese	Accuracy = 0.4209
Exp. No. 45	Blue channel	Bengali, Pakistani, Gilgit	Accuracy = 0.5670
Exp. No. 46	Blue channel	Bengali, Chinese, Gilgit	Accuracy = 0.6287
Exp. No. 47	Blue channel	Indian, Pakistani, Chinese	Accuracy = 0.4582
Exp. No. 48	Blue channel	Indian, Pakistani, Gilgit	Accuracy 0.5290
Exp. No. 49	Blue channel	Indian, Chinese, Gilgit	Accuracy = 0.6699
Exp. No. 50	Blue channel	Pakistani, Chinese, Gilgit	Accuracy = 0.6171
Exp. No. 51	Blue channel	Bengali, Indian, Pakistani	Accuracy = 0.3991
Exp. No. 52	Blue channel	Bengali, Indian, Chinese	Accuracy = 0.4388
Exp. No. 53	Blue channel	Bengali, Indian, Gilgit	Accuracy = 0.5038
Exp. No. 54	Blue channel	Bengali, Pakistani, Chinese	Accuracy = 0.4012
Exp. No. 55	Blue channel	Bengali, Pakistani, Gilgit	Accuracy = 0.5078
Exp. No. 56	Blue channel	Bengali, Chinese, Gilgit	Accuracy= 0.6287
Exp. No. 57	Blue channel	Indian, Pakistani, Chinese	Accuracy = 0.4226
Exp. No. 58	Blue channel	Indian, Pakistani, Gilgit	Accuracy = 0.5290
Exp. No. 59	Blue channel	Indian, Chinese, Gilgit	Accuracy = 0.5948
Exp. No. 60	Blue channel	Pakistani, Chinese, Gilgit	Accuracy = 0.5289
Exp. No. 61	Intensity Channel	Bengali, Indian, Pakistani	Accuracy = 0.3899
Exp. No. 62	Intensity Ch annel	Bengali, Indian, Chinese	Accuracy = 0.3932
Exp. No. 63	Intensity Channel	Bengali, Indian, Gilgit	Accuracy = 0.5076
Exp. No. 64	Intensity Channel	Bengali, Pakistani, Chinese	Accuracy = 0.4012
Exp. No. 65	Intensity Channel	Bengali, Pakistani, Gilgit	Accuracy =0.5576
Exp. No. 66	Intensity Channel	Bengali, Chinese, Gilgit	Accuracy = 0.5889
Exp. No. 67	Intensity Channel	Indian, Pakistani, Chinese	Accuracy = 0.3933
Exp. No. 68	Intensity Channel	Indian, Pakistani, Gilgit	Accuracy= 0.6007
Exp. No. 69	Intensity Channel	Indian, Chinese, Gilgit	Accuracy = 0.5621
Exp. No. 70	Intensity Channel	Pakistani, Chinese, Gilgit	Accuracy = 0.6529
Exp. No. 71	Intensity Channel	Bengali, Indian, Pakistani	Accuracy = 0.3899
Exp. No. 72	Intensity Channel	Bengali, Indian, Chinese	Accuracy = 0.3942
Exp. No. 73	Intensity Channel	Bengali, Indian, Gilgit	Accuracy = 0.5076
Exp. No. 74	Intensity Channel	Bengali, Pakistani, Chinese	Accuracy = 0.4012
Exp. No. 75	Intensity Channel	Bengali, Pakistani, Gilgit	Accuracy = 0.5576
Exp. No. 76	Intensity Channel	Bengali, Chinese, Gilgit	Accuracy = 0.5689
Exp. No. 77	Intensity Channel	Indian, Pakistani, Chinese	Accuracy = 0.3933
Exp. No. 78	Intensity Channel	Indian, Pakistani, Gilgit	Accuracy = 0.5622
Exp. No. 79	Intensity Channel	Indian, Chinese, Gilgit	Accuracy = 0.5621
Exp. No. 80	Intensity Channel	Pakistani, Chinese, Gilgit	Accuracy = 0.5629
Exp. No. 81	RGB-Color	Bengali, Indian, Pakistani	Accuracy = 0.4676
Exp. No. 82	RGB-Color	Bengali, Indian, Chinese	Accuracy = 0.6271
Exp. No. 83	RGB-Color	Bengali, Indian, Gilgit	Accuracy = 0.6635
Exp. No. 84	RGB-Color	Bengali, Pakistani, Chinese	Accuracy = 0.5773
Exp. No. 85	RGB-Color	Bengali, Pakistani, Gilgit	Accuracy = 0.6253
Exp. No. 86	RGB-Color	Bengali, Chinese, Gilgit	Accuracy = 0.7836
Exp. No. 87	RGB-Color	Indian, Pakistani, Chinese	Accuracy = 0.6038
Exp. No. 88	RGB-Color	Indian, Pakistani, Gilgit	Accuracy = 0.6477

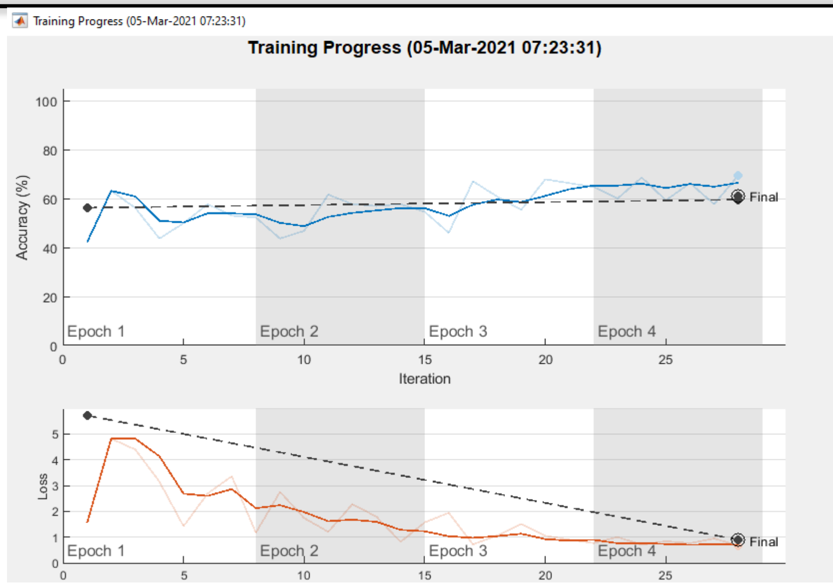
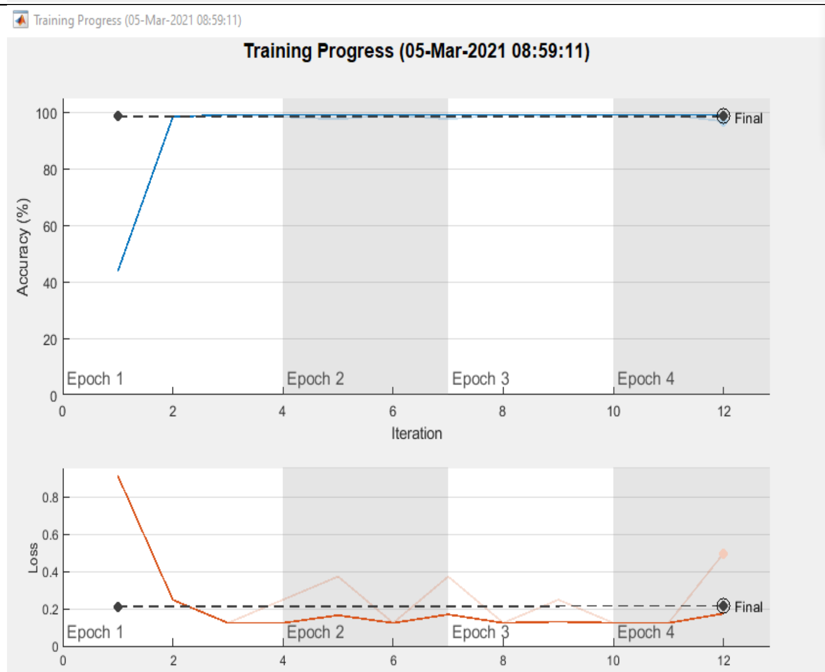
Exp. No. 89	RGB-Color	Indian, Chinese, Gilgit	Accuracy = 0.7520
Exp. No. 90	RGB-Color	Pakistani, Chinese, Gilgit	Accuracy = 0.7477
Exp. No. 91	RGB-Color	Bengali, Indian, Pakistani	Accuracy = 0.6733
Exp. No. 92	RGB-Color	Bengali, Indian, Chinese	Accuracy = 0.7520
Exp. No. 93	RGB-Color	Bengali, Indian, Gilgit	Accuracy = 0.6824
Exp. No. 94	RGB-Color	Bengali, Pakistani, Chinese	Accuracy = 0.6102
Exp. No. 95	RGB-Color	Bengali, Pakistani, Gilgit	Accuracy = 0.6433
Exp. No. 96	RGB-Color	Bengali, Chinese, Gilgit	Accuracy = 0.7811
Exp. No. 97	RGB-Color	Indian, Pakistani, Chinese	Accuracy = 0.6195
Exp. No. 98	RGB-Color	Indian, Pakistani, Gilgit	Accuracy = 0.6733
Exp. No. 99	RGB-Color	Indian, Chinese, Gilgit	Accuracy = 0.7520
Exp. No. 100	RGB-Color	Pakistani, Chinese, Gilgit	Accuracy = 0.7477
Exp. No. 101	Red channel	Bengali, Indian, Chinese, Pakistani	Accuracy = 0.5160
Exp. No. 102	Red channel	Bengali, Indian, Chinese, Gilgit	Accuracy = 0.6052
Exp. No. 103	Green channel	Bengali, Indian, Chinese, Pakistani	Accuracy = 0.3307
Exp. No. 104	Green channel	Bengali, Indian, Chinese, Gilgit	Accuracy = 0.3570
Exp. No. 105	Blue channel	Bengali, Indian, Chinese, Pakistani	Accuracy = 0.3403
Exp. No. 106	Blue channel	Bengali, Indian, Chinese, Gilgit	Accuracy = 0.4545
Exp. No. 107	Intensity channel	Bengali, Indian, Chinese, Pakistani	Accuracy = 0.3321
Exp. No. 108	Intensity channel	Bengali, Indian, Chinese, Gilgit	Accuracy = 0.2960
Exp. No. 109	RGB-Color	Bengali, Indian, Chinese, Pakistani	Accuracy = 0.4913
Exp. No. 110	RGB-Color	Bengali, Indian, Chinese, Gilgit	Accuracy = 0.5140
Exp. No. 111	Red channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Accuracy = 0.3360
Exp. No. 112	Green channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Accuracy = 0.3966
Exp. No. 113	Blue channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Accuracy=0.3040
Exp. No. 114	Intensity channel	Bengali, Indian, Pakistani, Chinese, Gilgit	Accuracy =0.3040
Exp. No. 115	RGB-Color	Bengali, Indian, Pakistani, Chinese, Gilgit	Accuracy = 0.3834

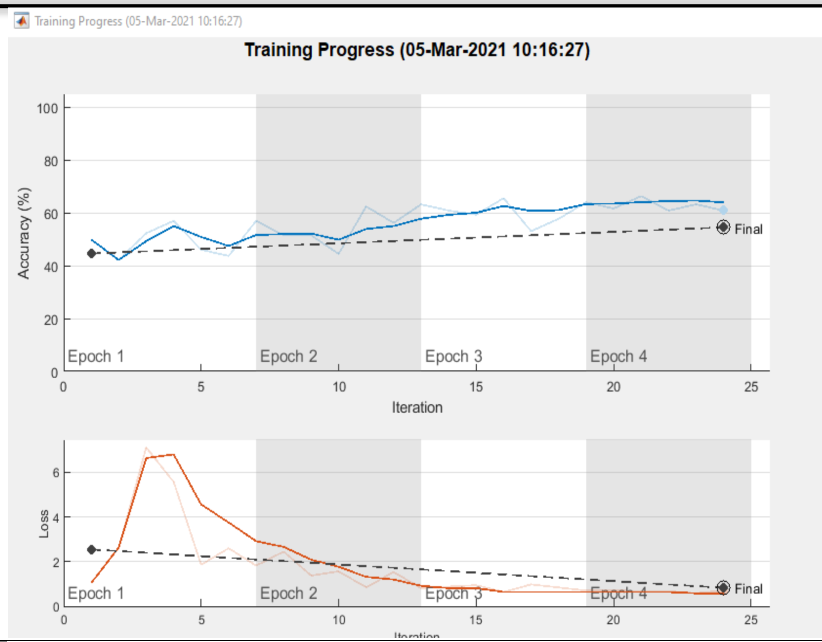
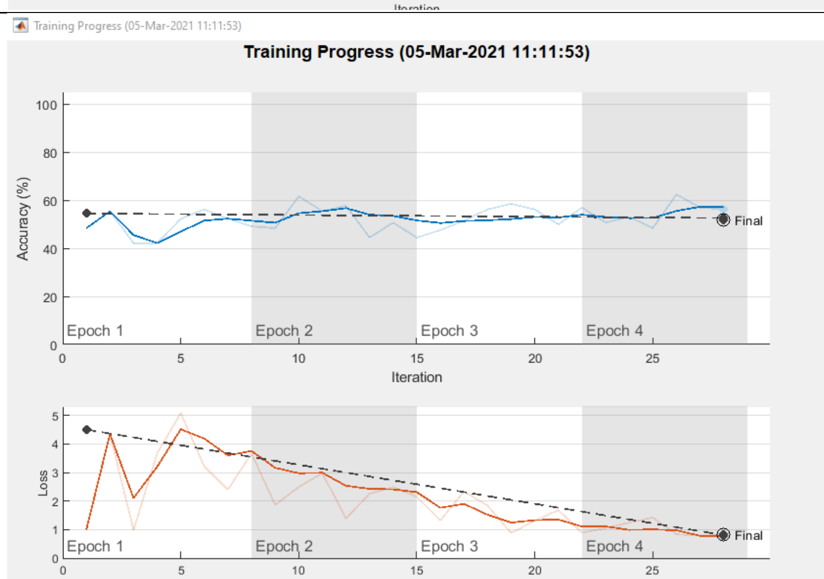
Table 7 Accuracy loss plots in graphs of the results of the experiments obtained through the proposed model for different experiments on each of the red, green, blue, intensity, and color channel of the dataset under experiments.

Experiment No.	Accuracy loss plot of the experiment

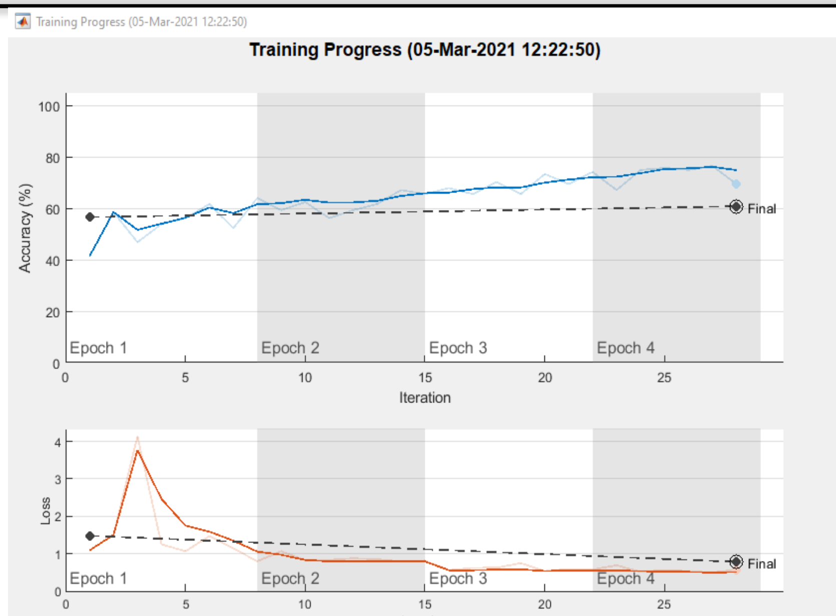
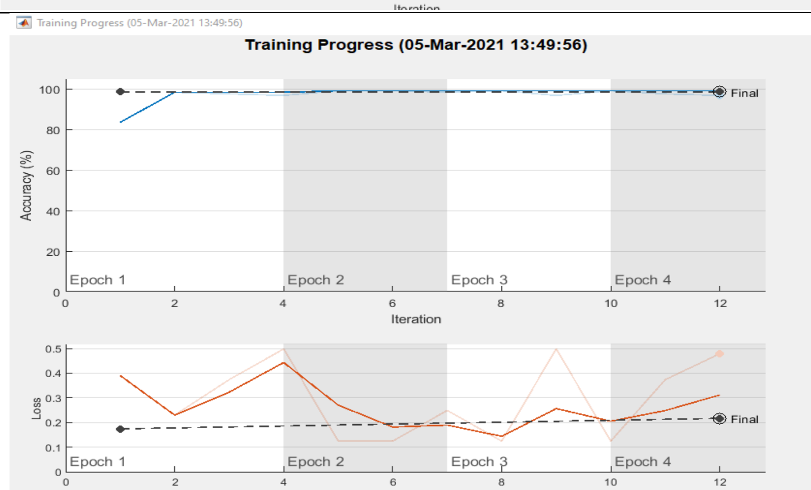
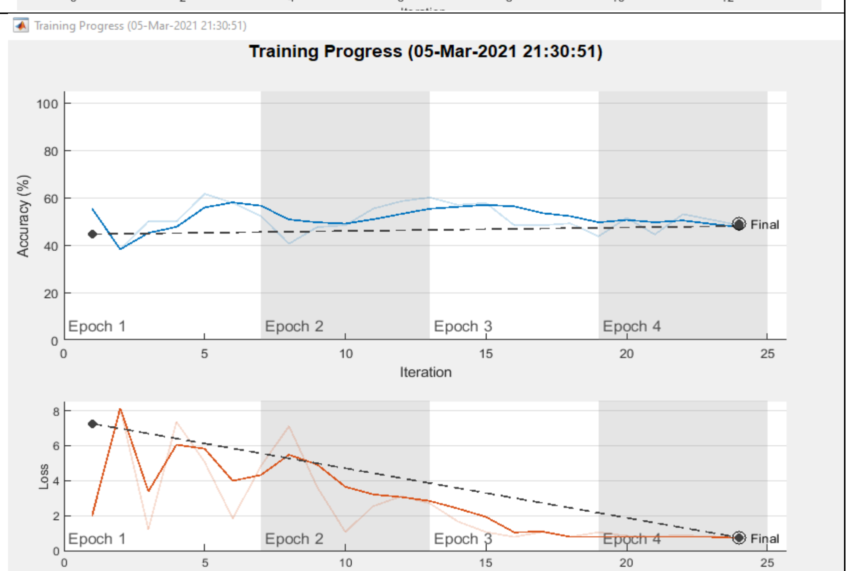
Exp. No. 01	
Exp. No. 02	
Exp. No. 03	

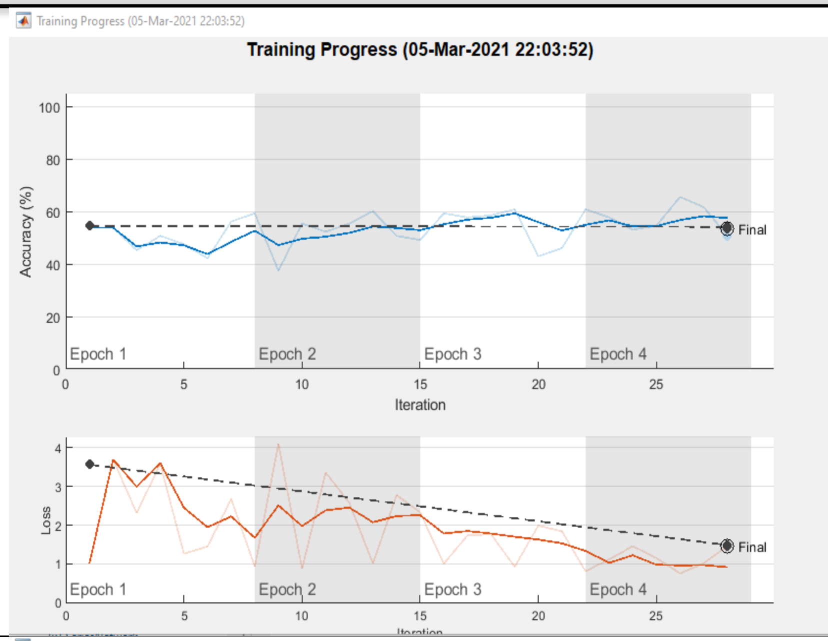
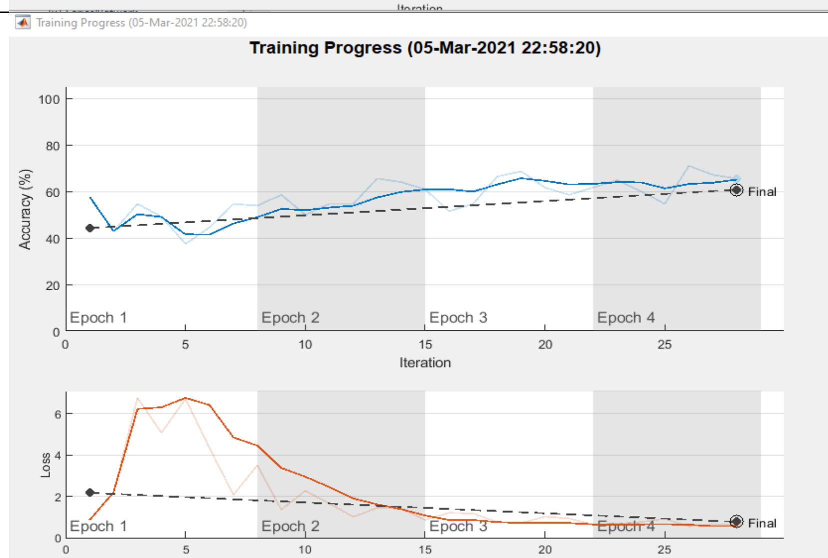
Exp. No. 04	
Exp. No. 05	
Exp. No. 06	

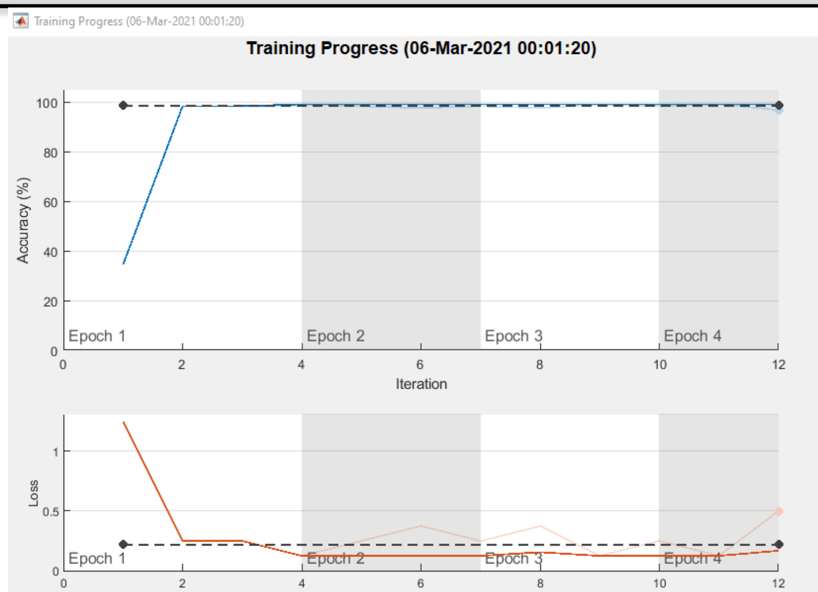
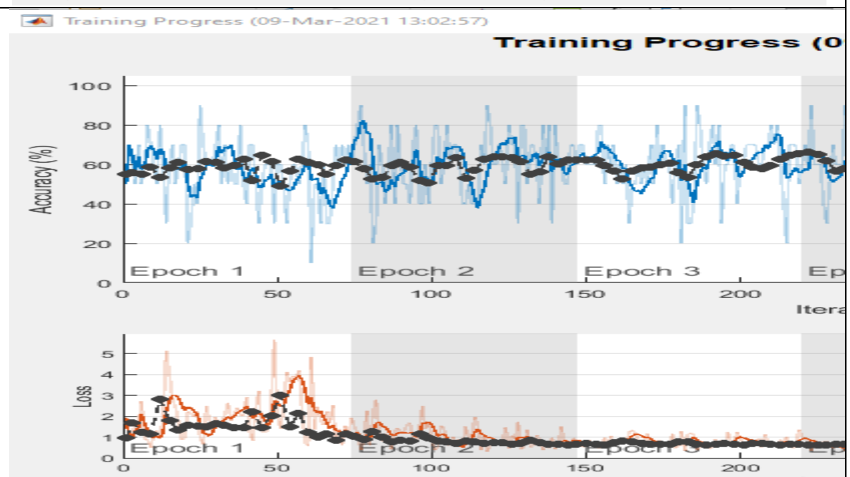
Exp. No. 07	
Exp. No. 08	

Exp. No. 09	
Exp. No. 10	

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 3, Issue 9, 2025

Exp. No. 11	
Exp. No. 12	
Exp. No. 13	

Exp. No. 14	
Exp. No. 15	

Exp. No. 16	
Exp. No. 17	

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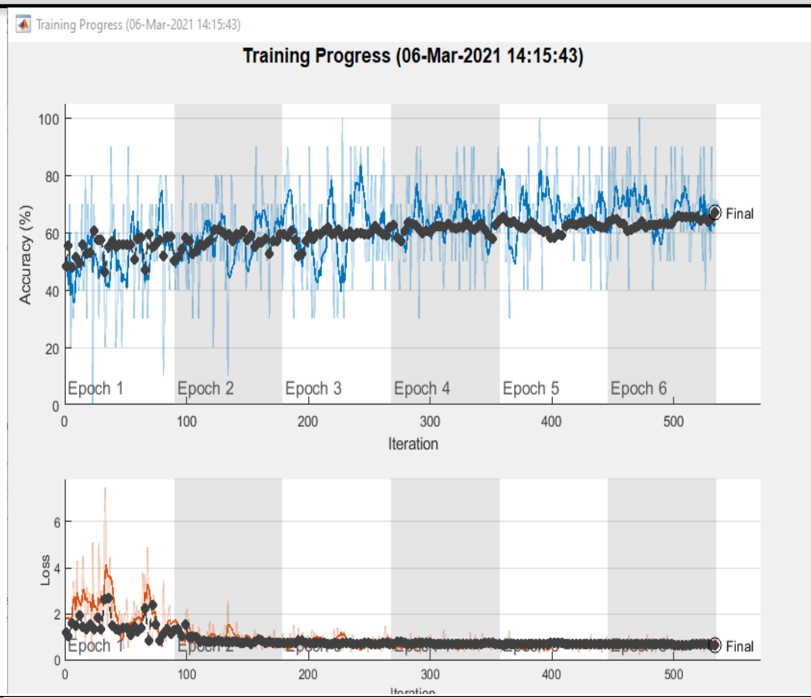
<tr><td>Exp. No. 18</td><td>
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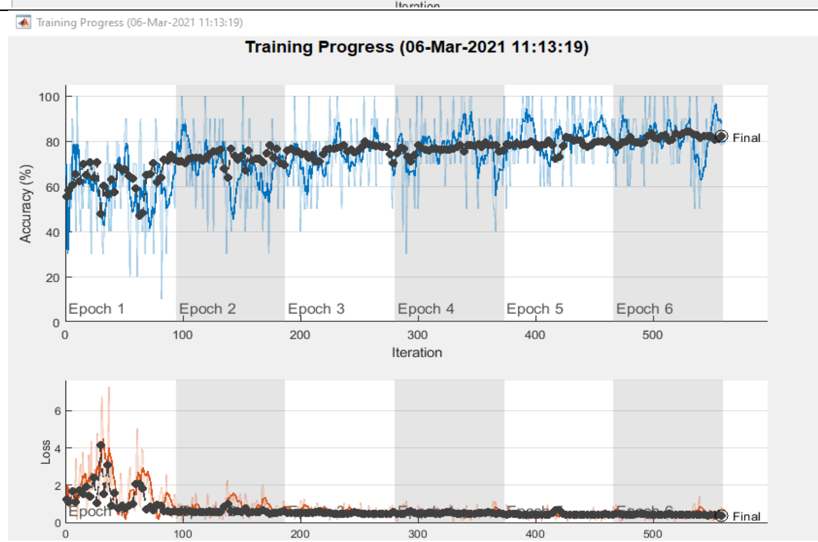
<tr><td>Exp. No. 19</td><td>
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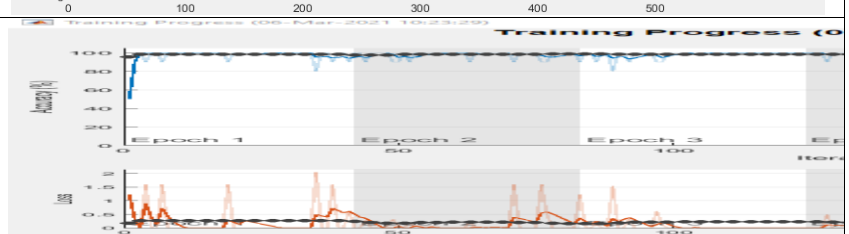
<tr><td>Exp. No. 20</td><td>
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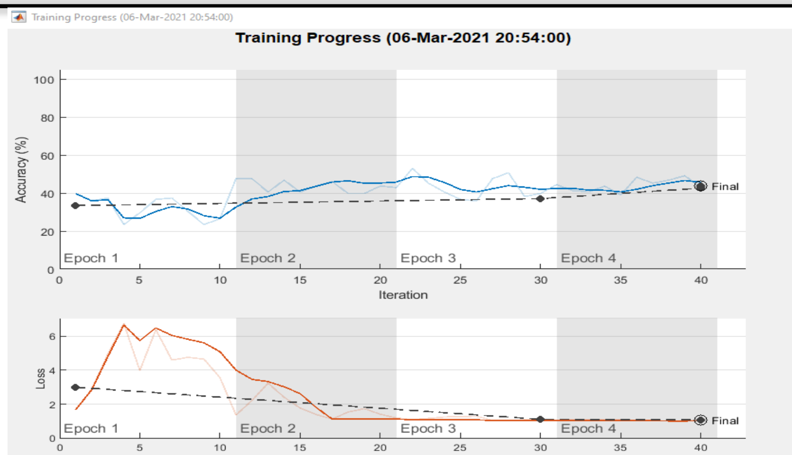
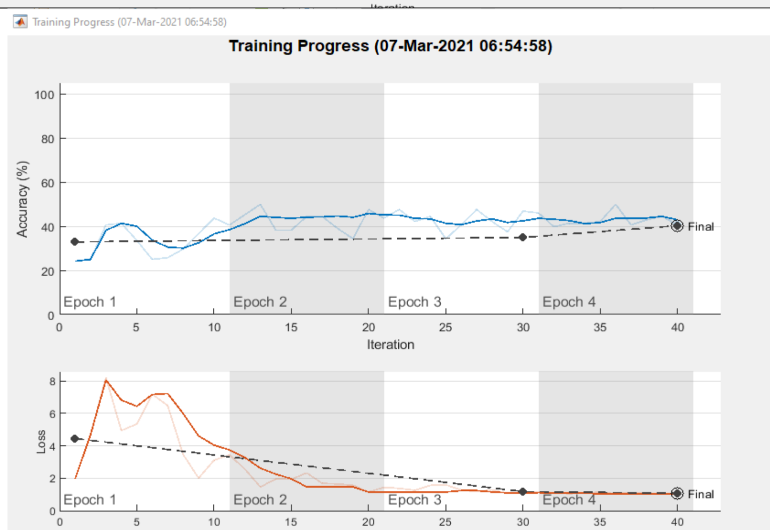
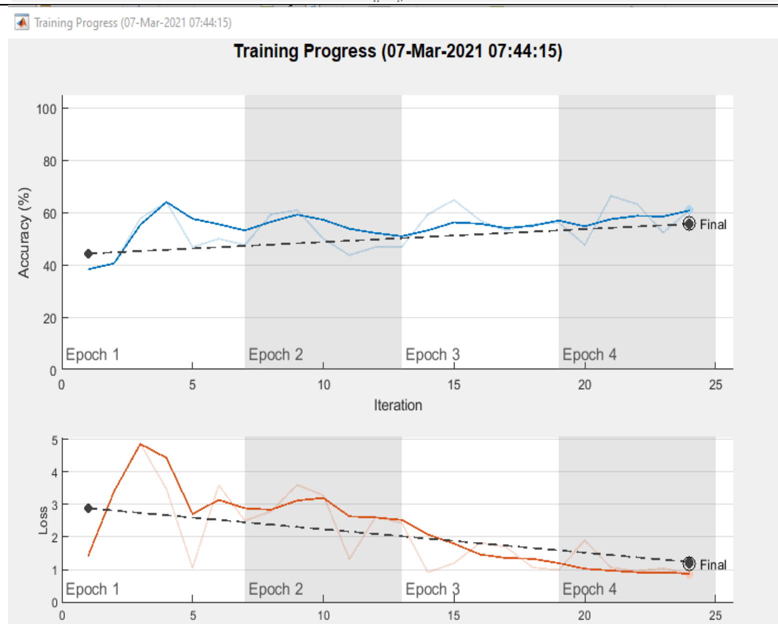
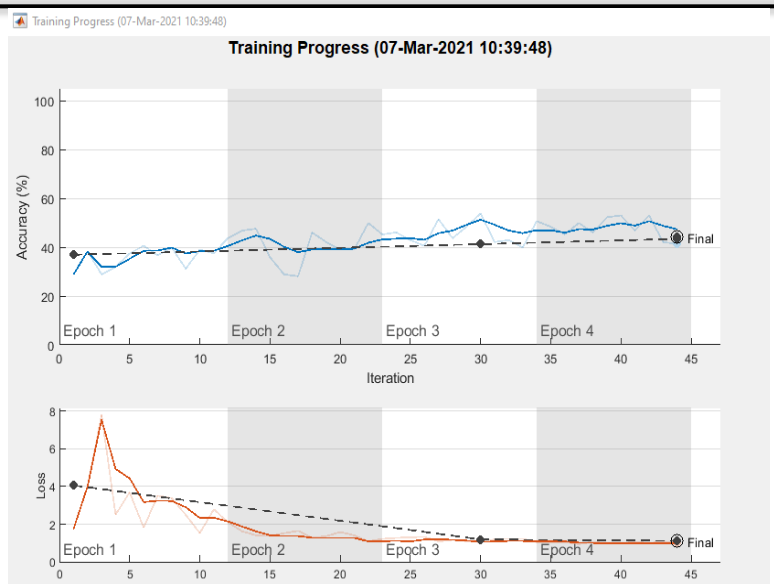
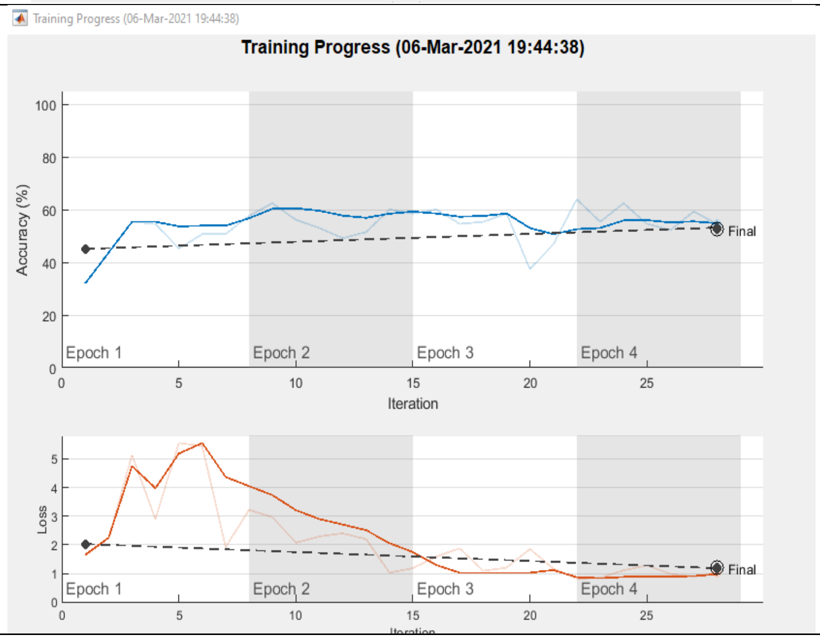
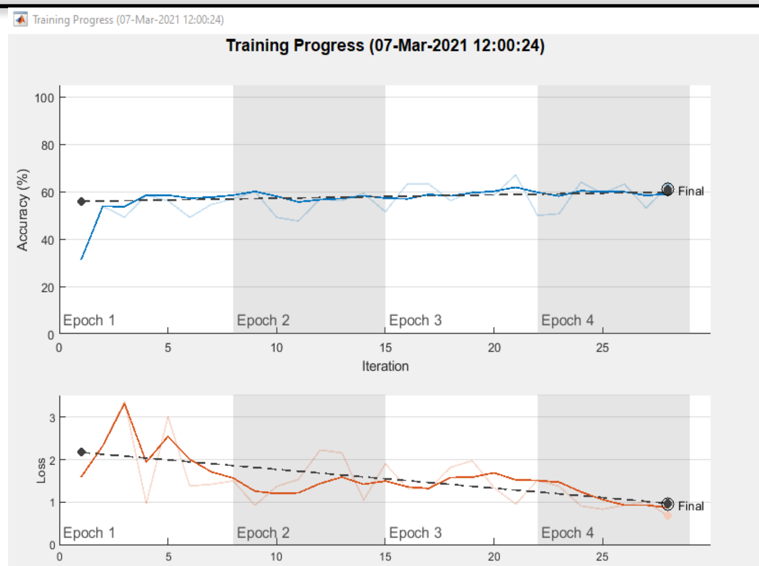
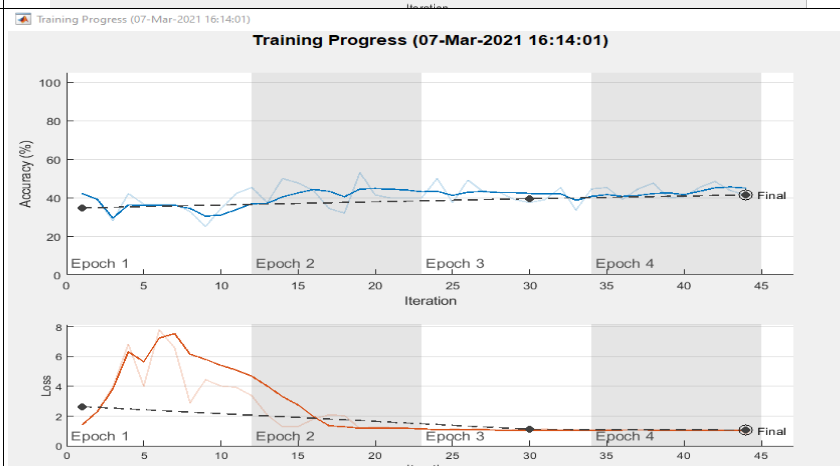
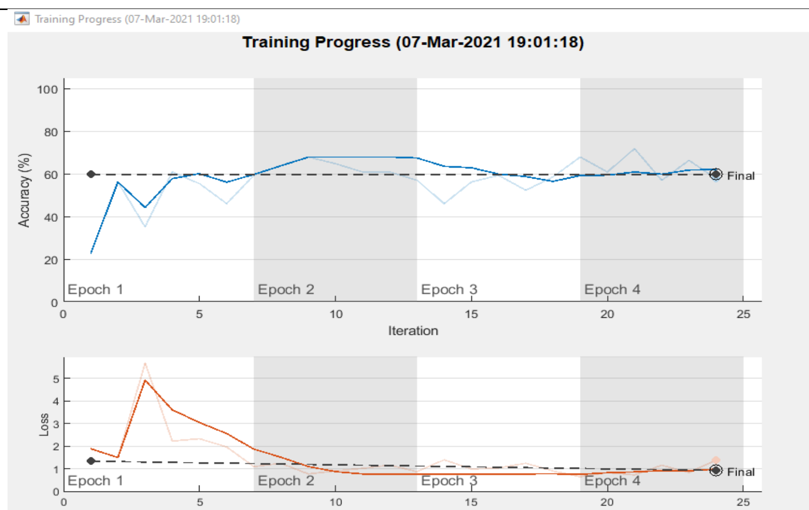
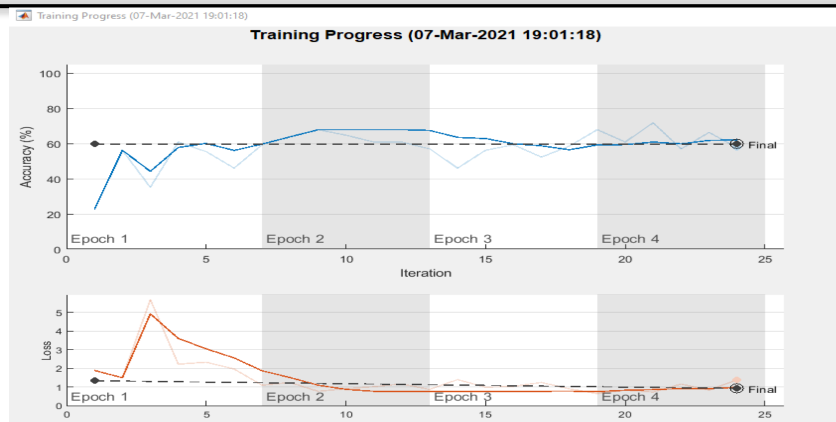
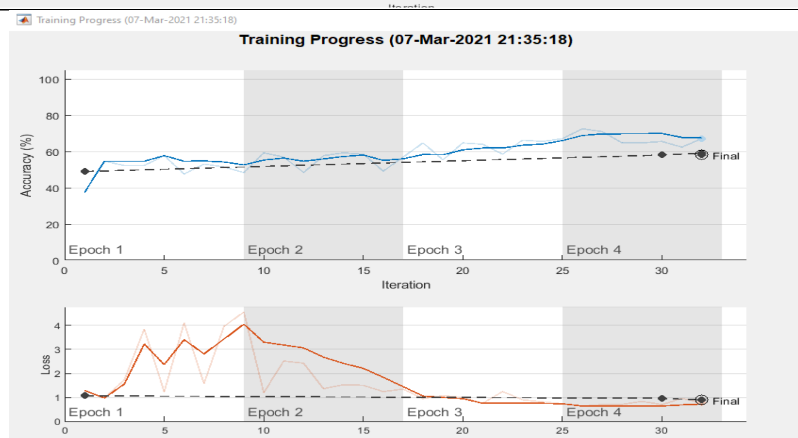
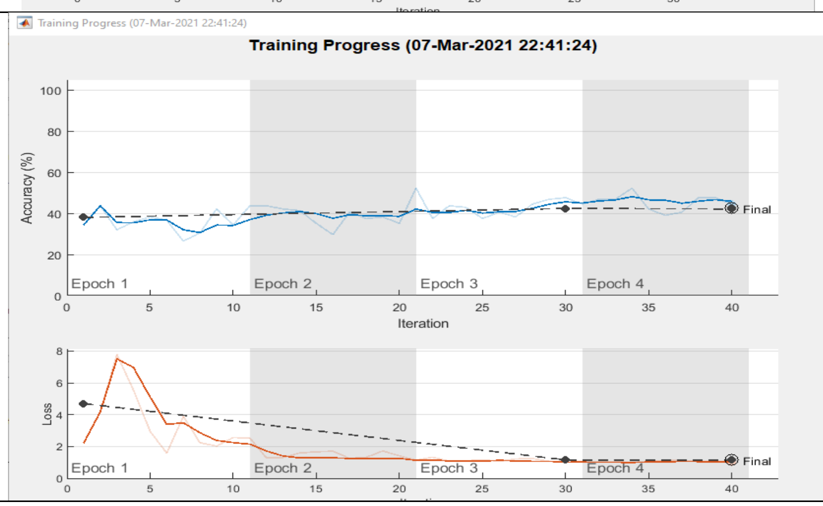
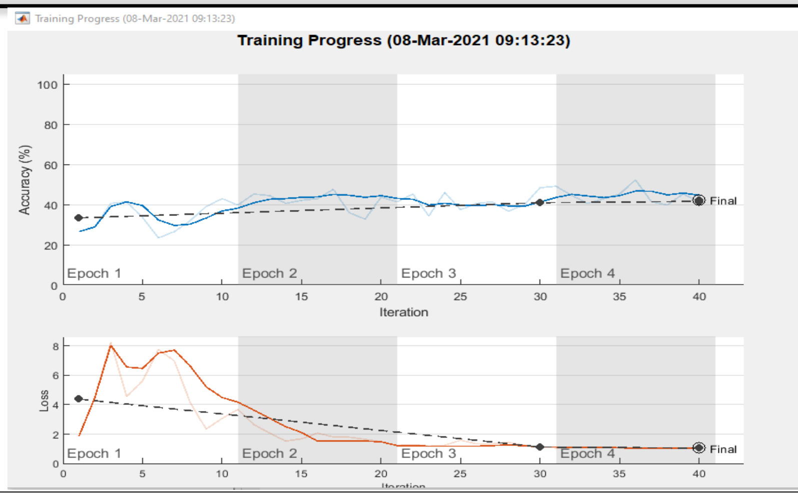
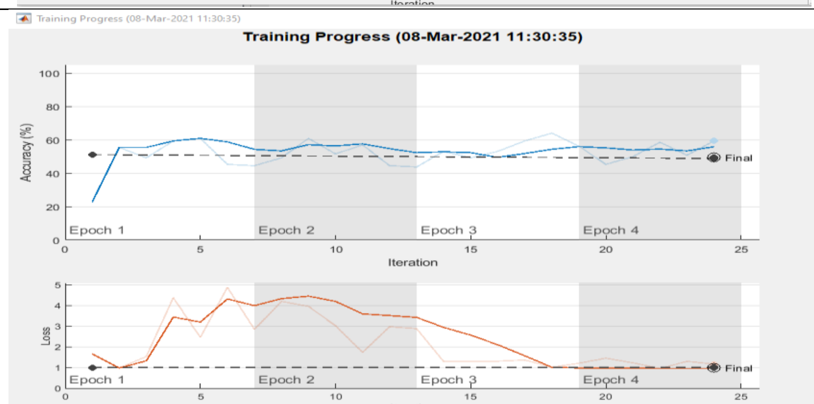
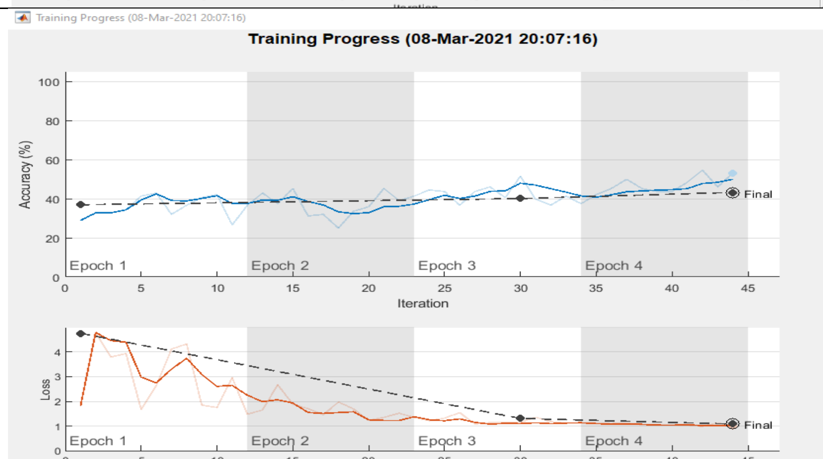
Exp. No. 21	
Exp. No. 22	
Exp. No. 23	

Exp. No. 24	
Exp. No. 25	

Exp. No. 26	
Exp. No. 27	
Exp. No. 28	

Exp. No. 29	
Exp. No. 30	
Exp. No. 31	

Exp. No. 32	
Exp. No. 33	
Exp. No. 34	

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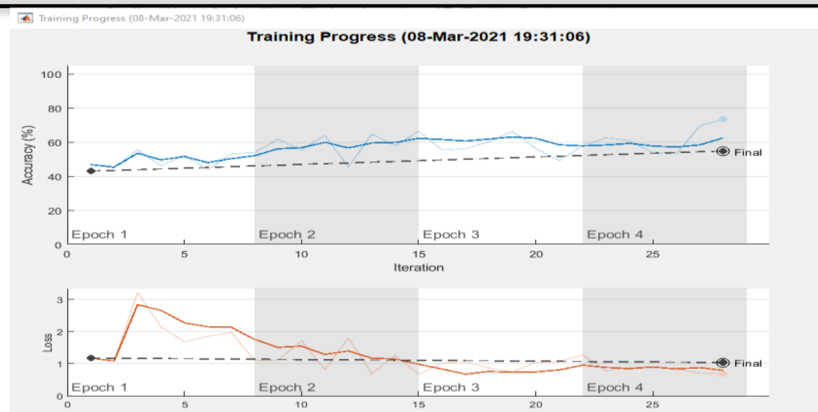

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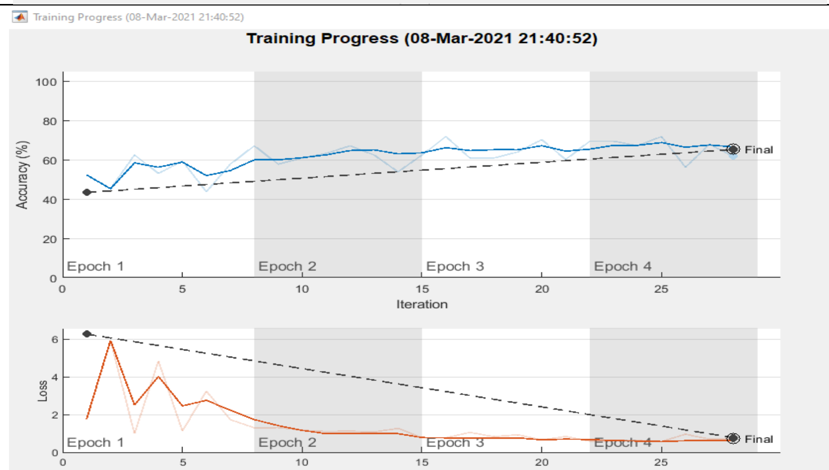

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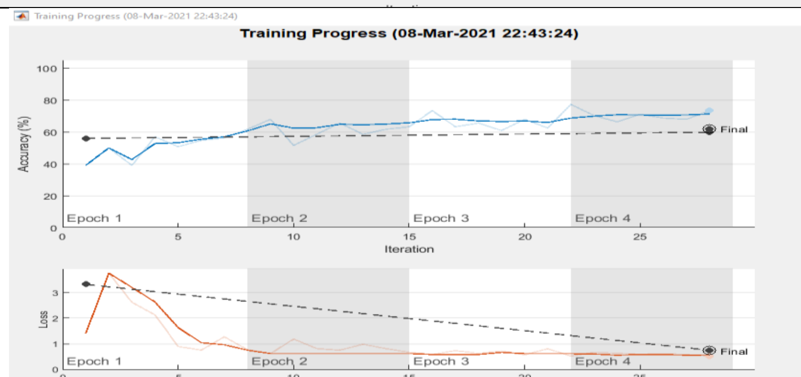

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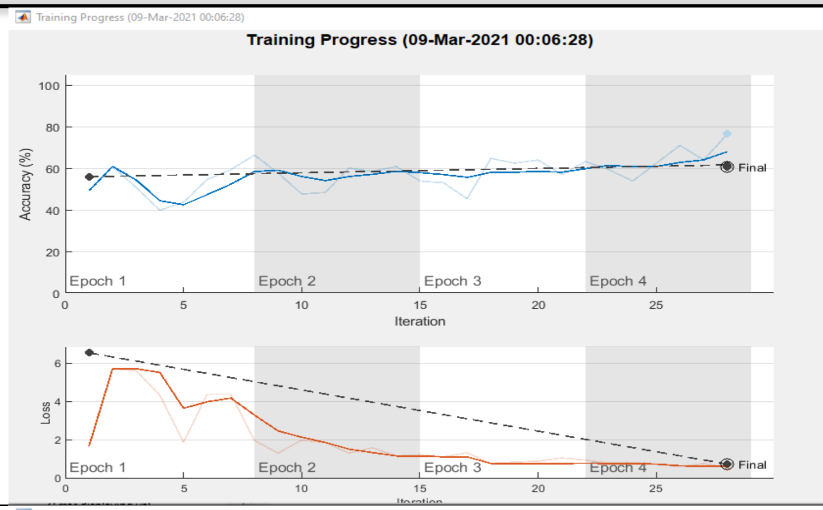
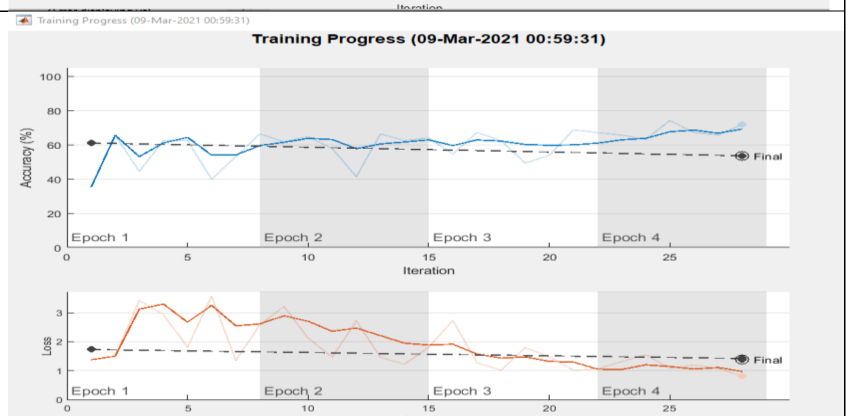
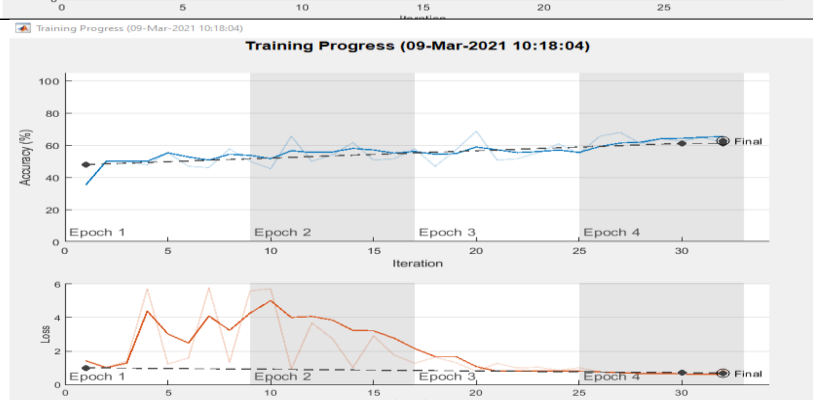
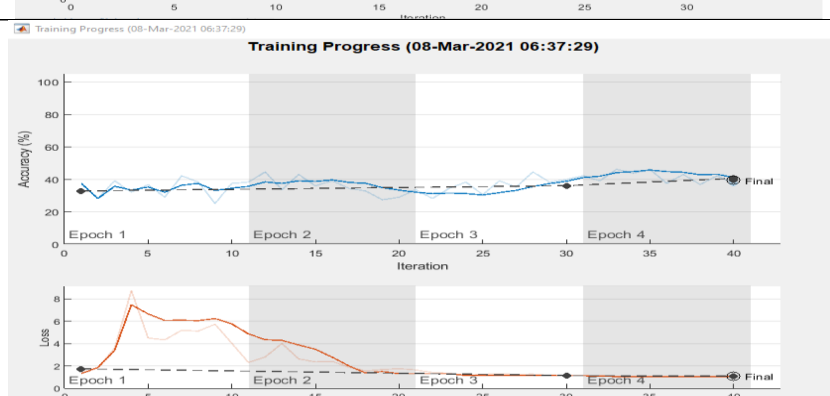
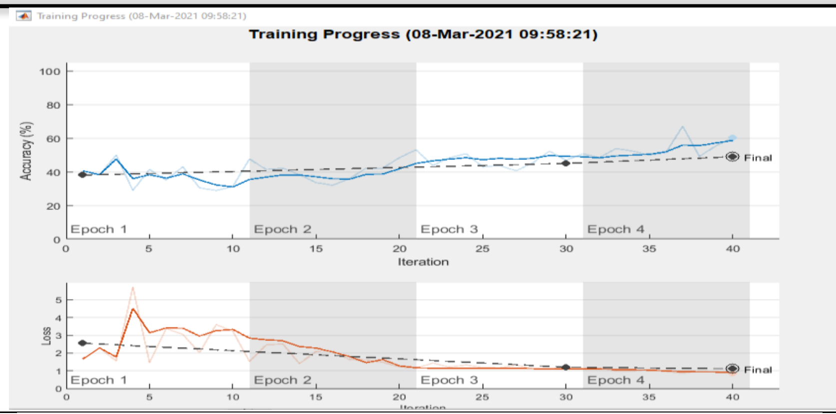
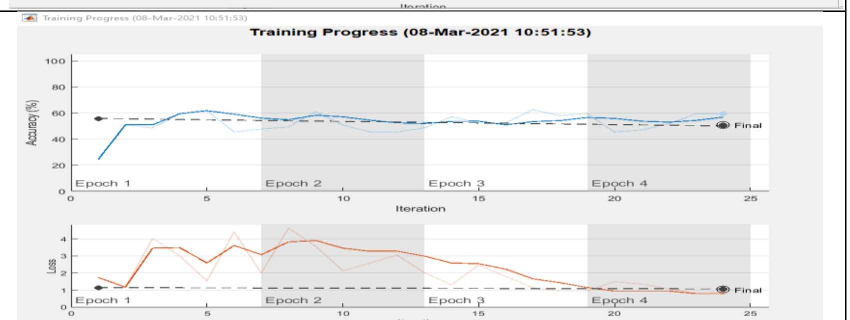
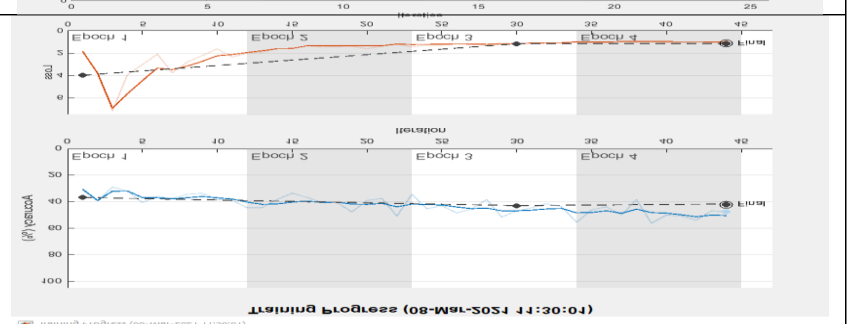
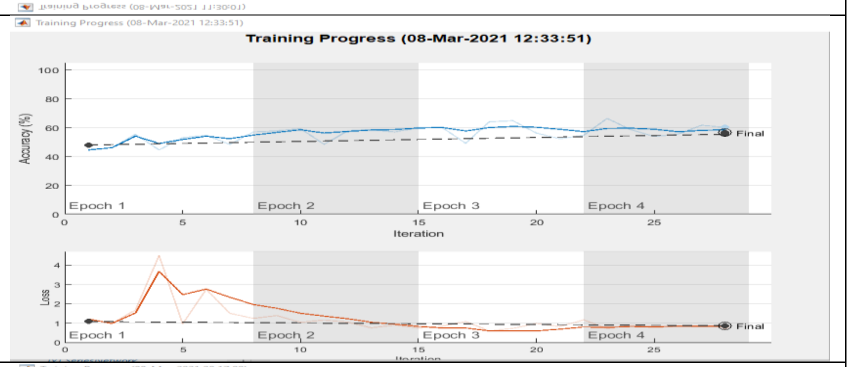
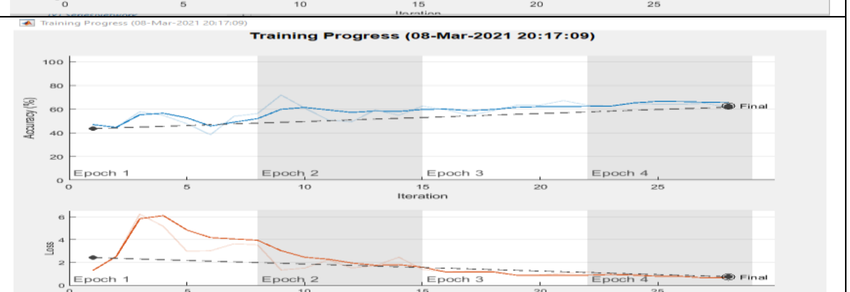
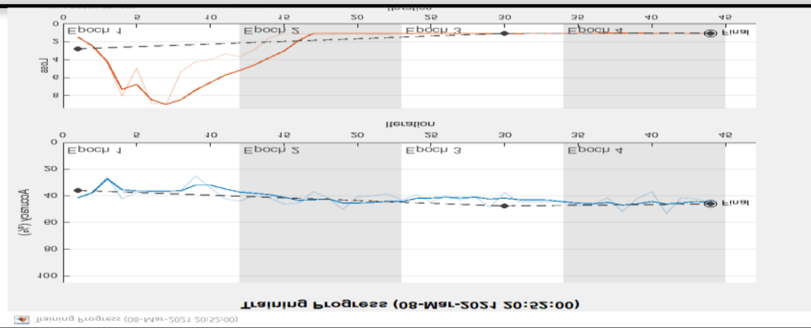
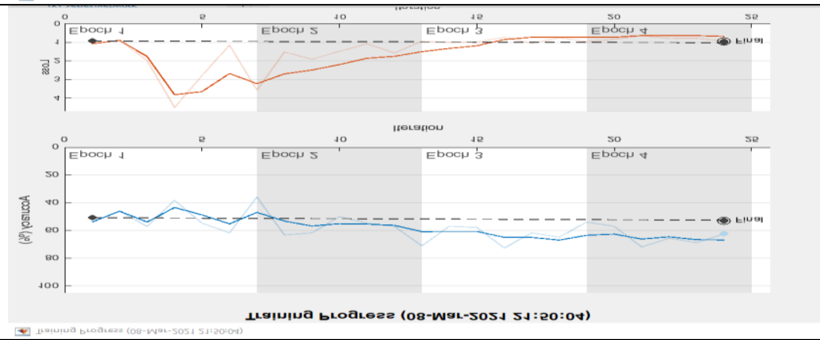
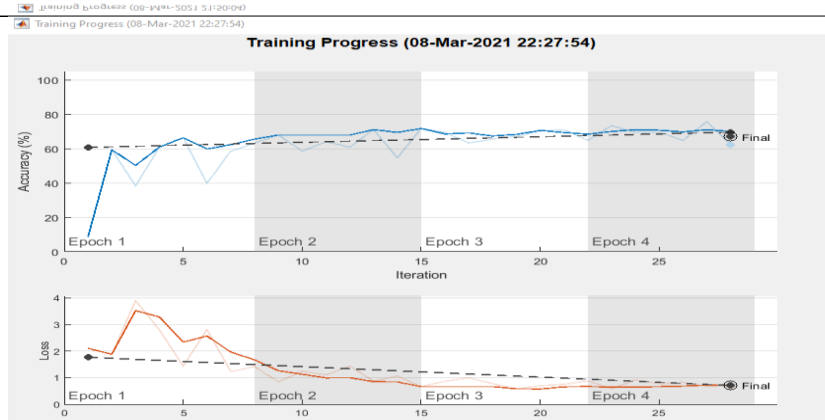
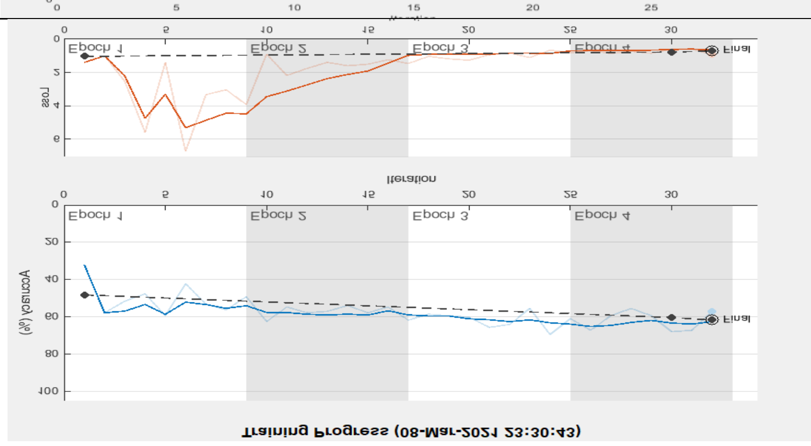
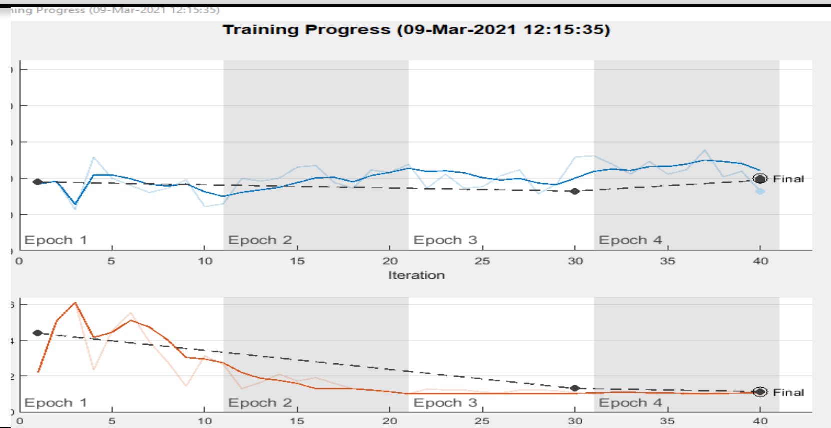
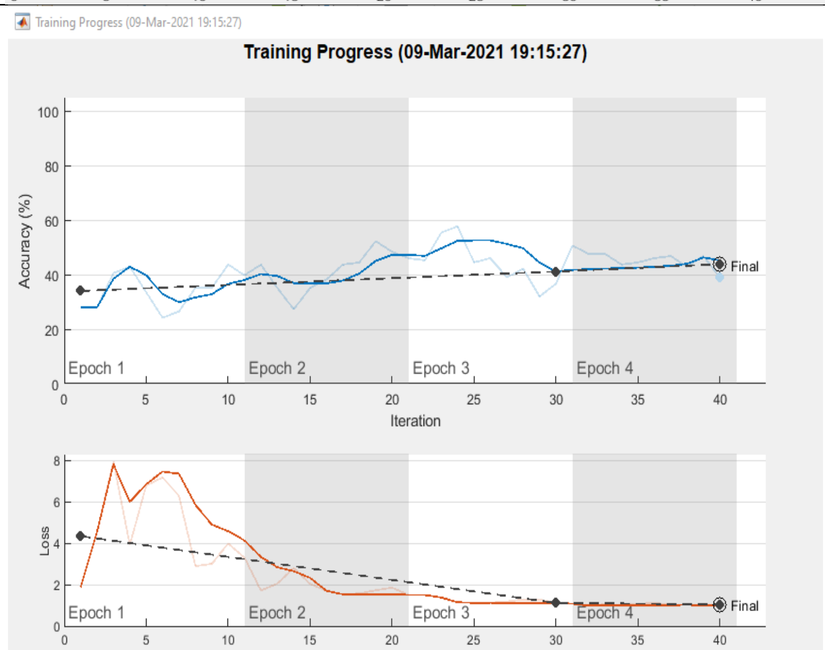
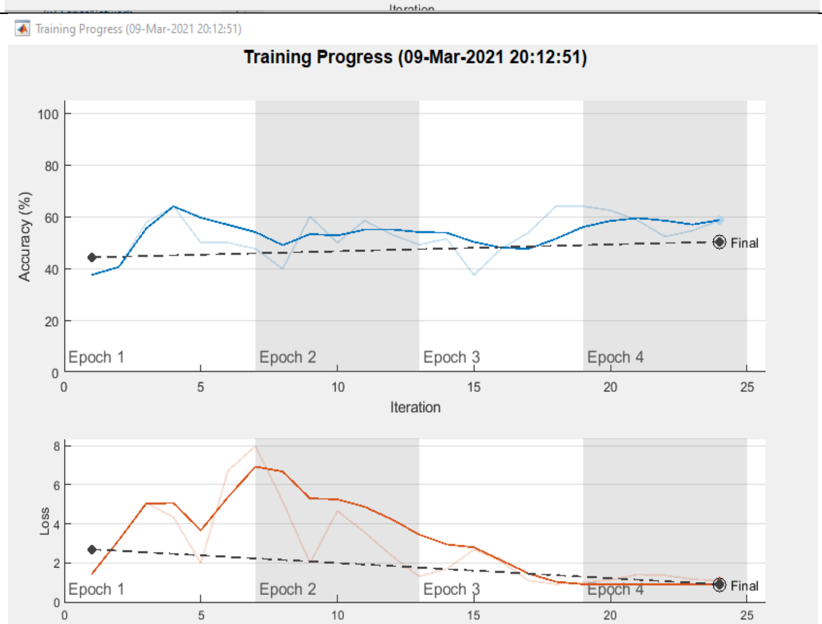
Exp. No. 38	
Exp. No. 39	
Exp. No. 40	
Exp. No. 41	

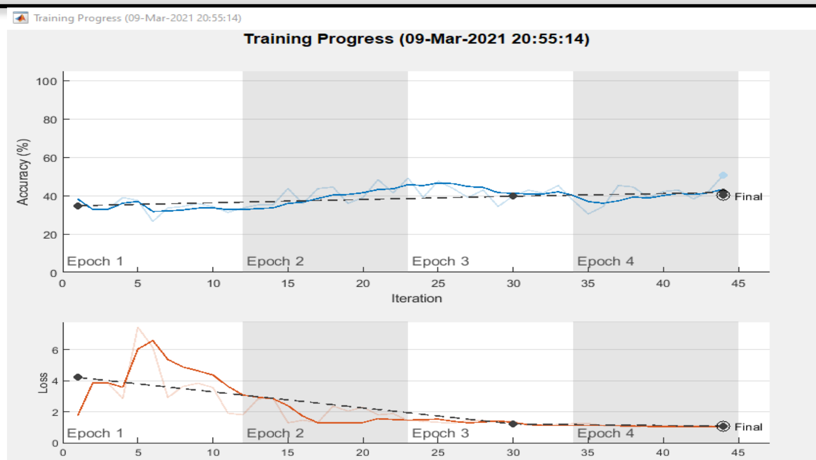
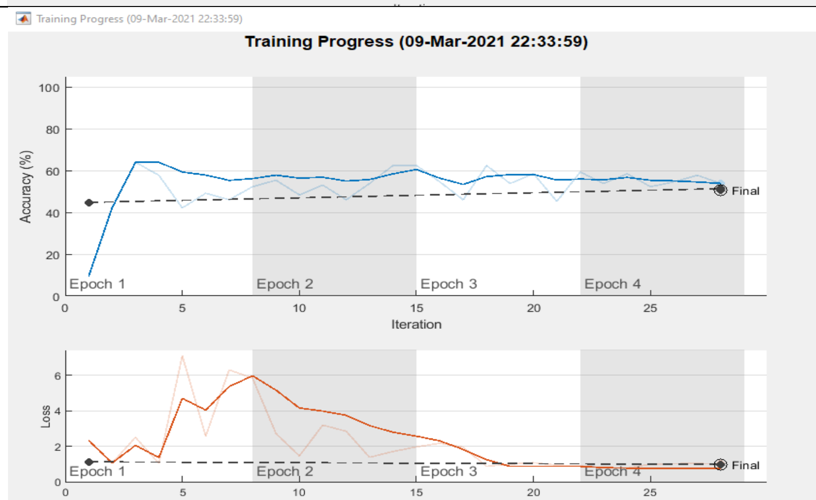
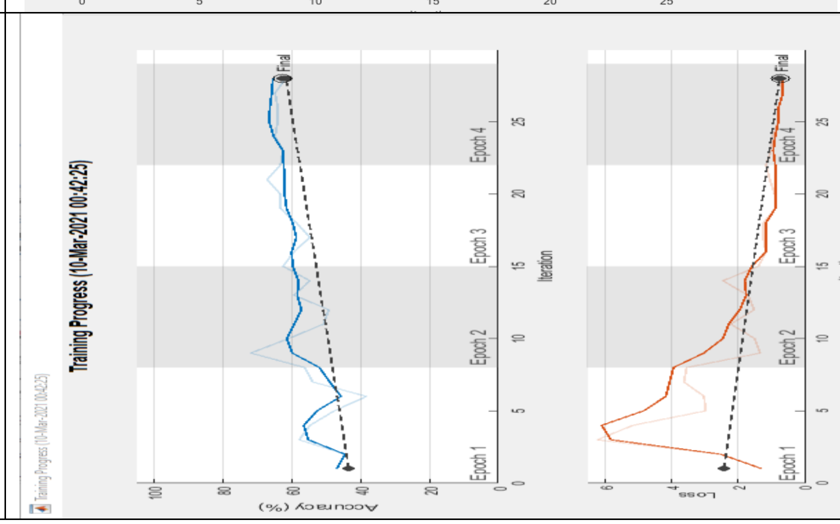
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 9, 2025

Exp. No. 42	
Exp. No. 43	
Exp. No. 44	
Exp. No. 45	
Exp. No. 46	

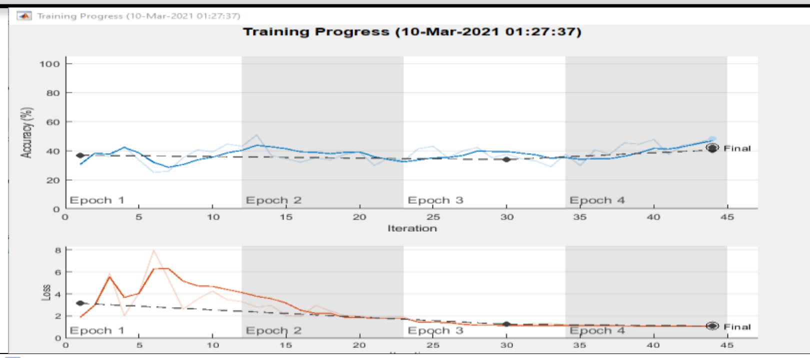
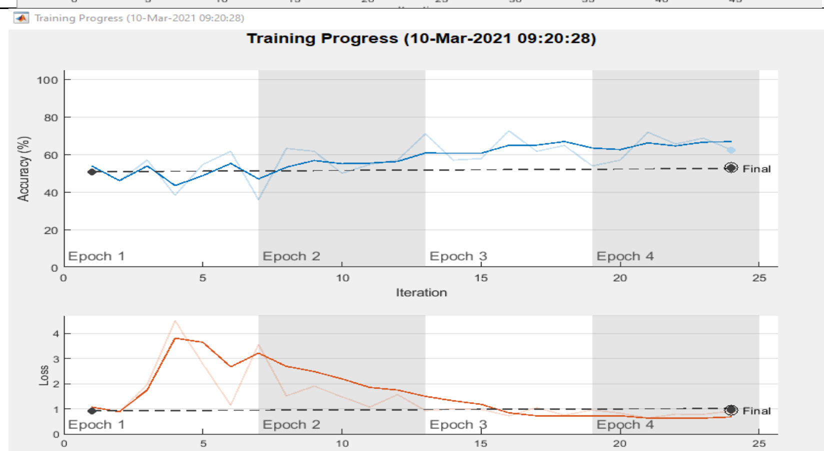
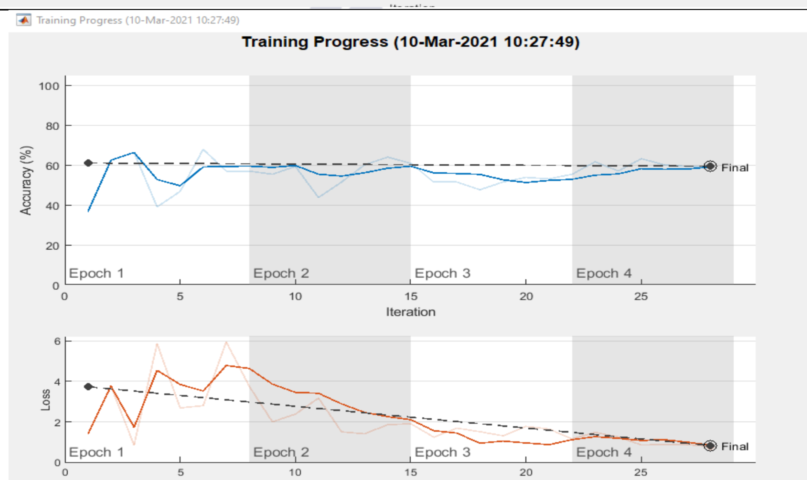
Exp. No. 47	
Exp. No. 48	
Exp. No. 49	
Exp. No. 50	

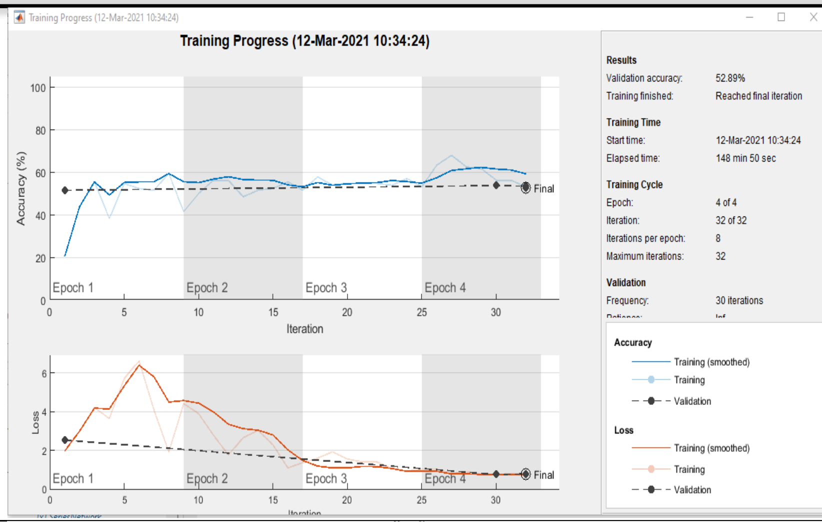
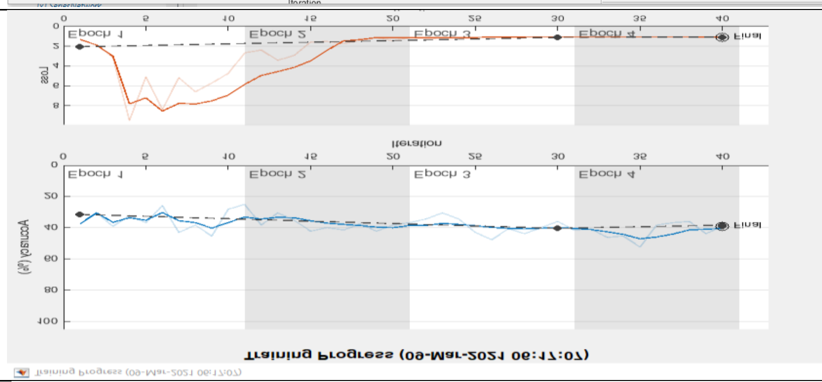
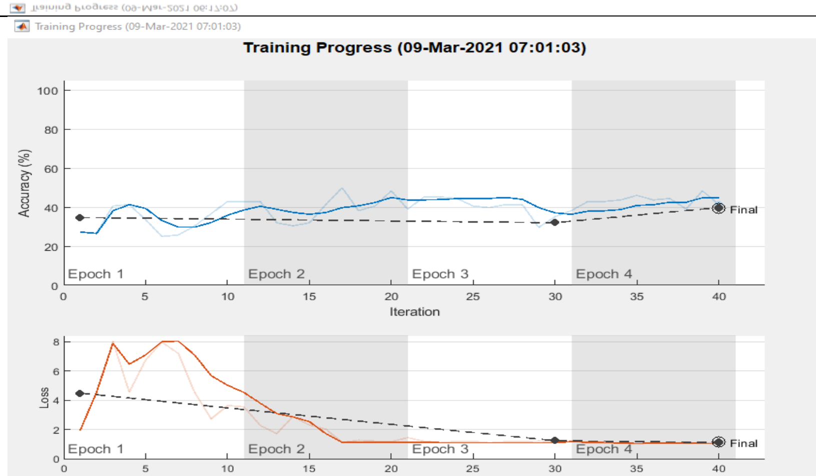
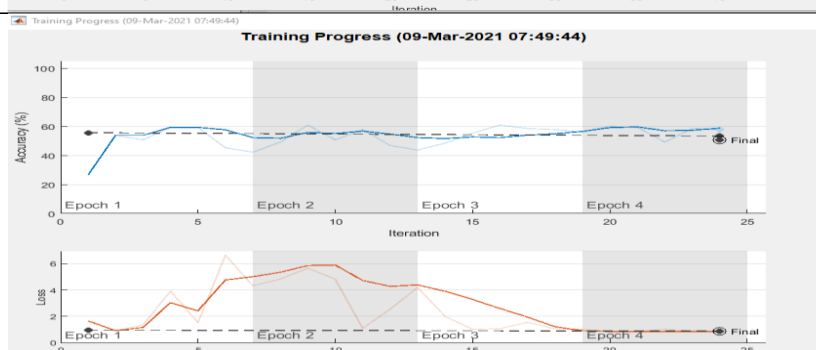
Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 9, 2025

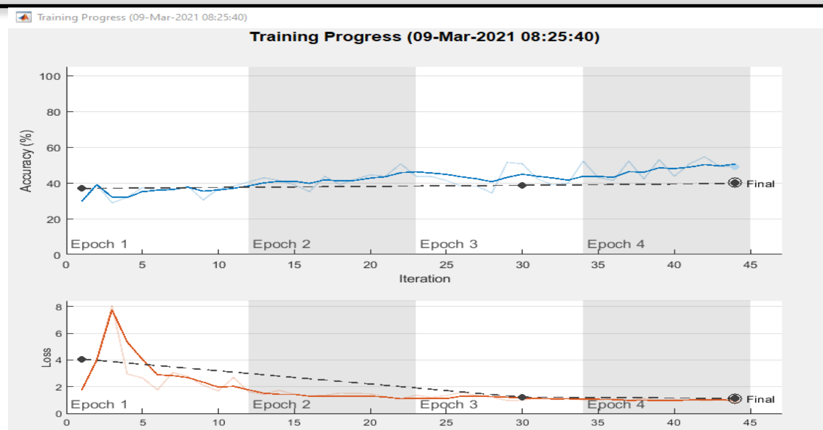
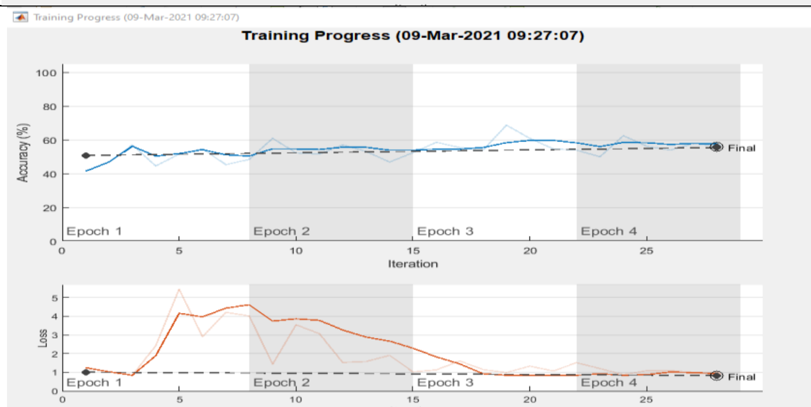
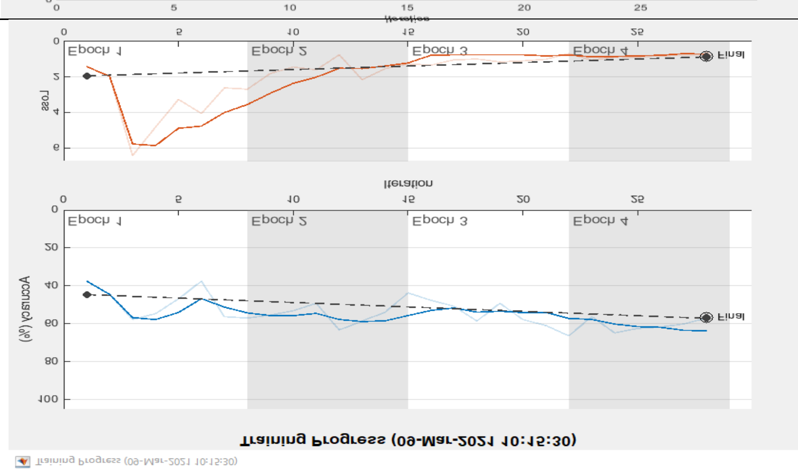
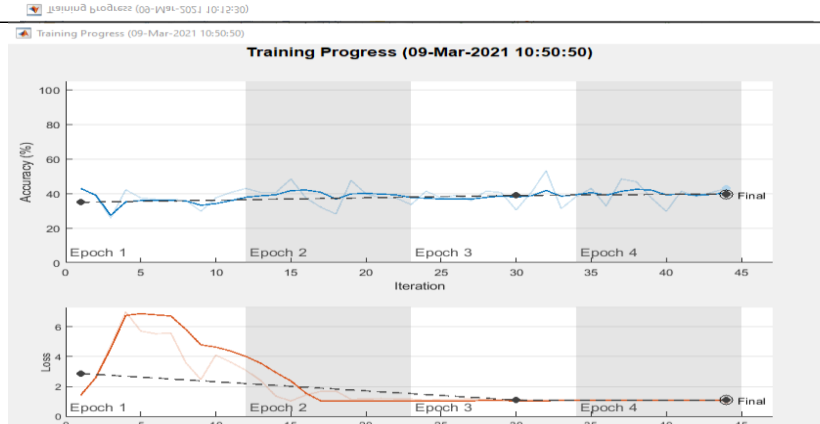
Exp. No. 51	
Exp. No. 52	
Exp. No. 53	

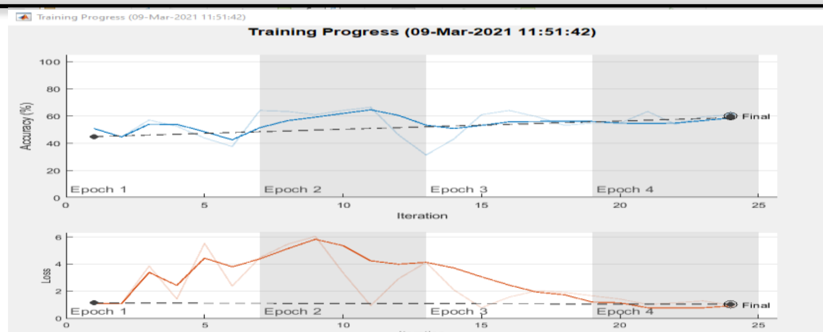
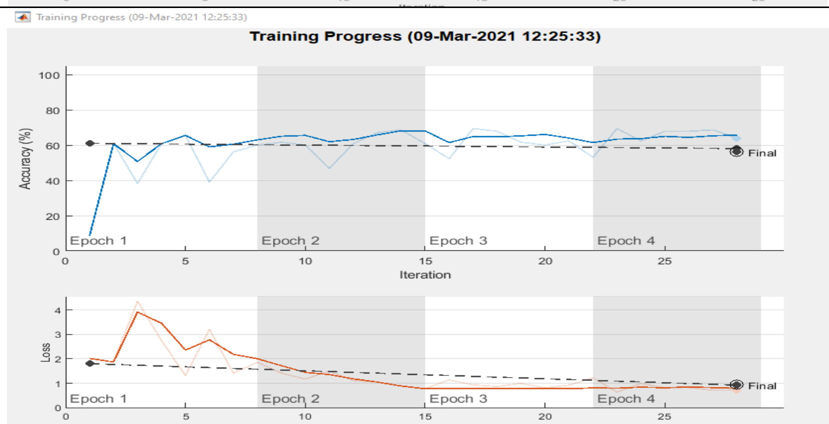
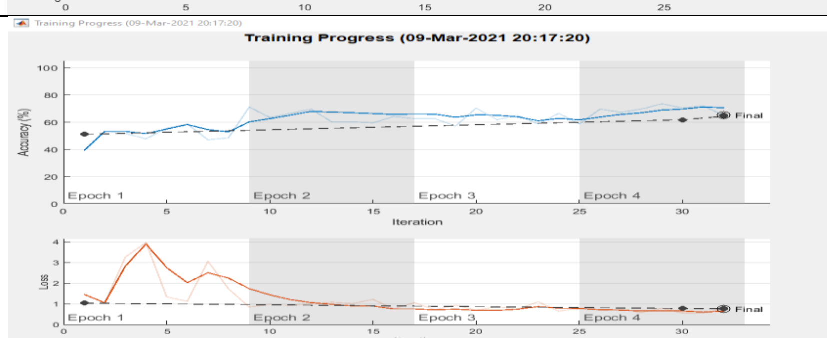
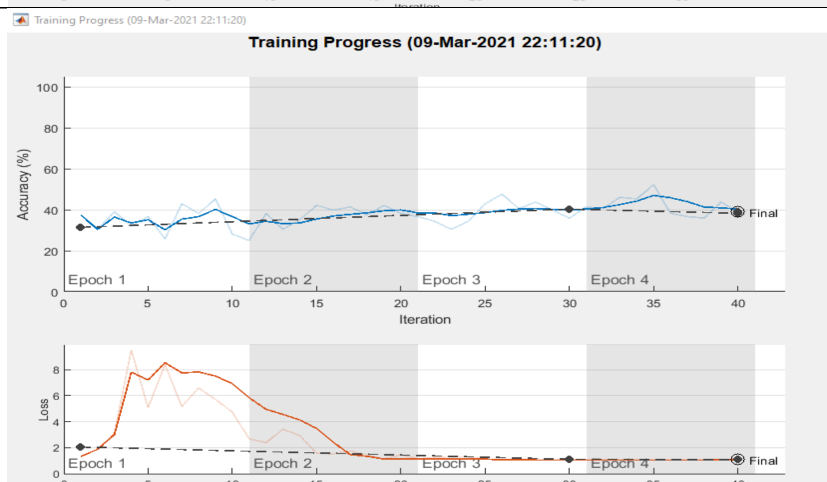
Exp. No. 54	
Exp. No. 55	
Exp. No. 56	

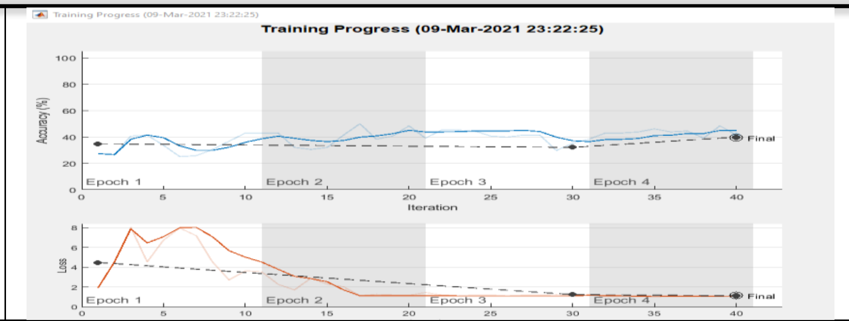
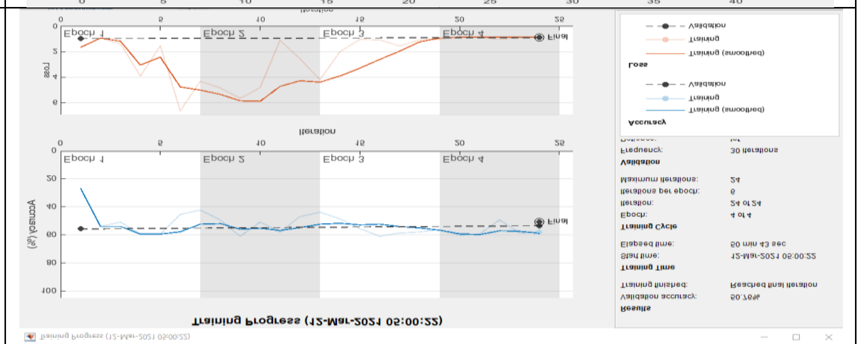
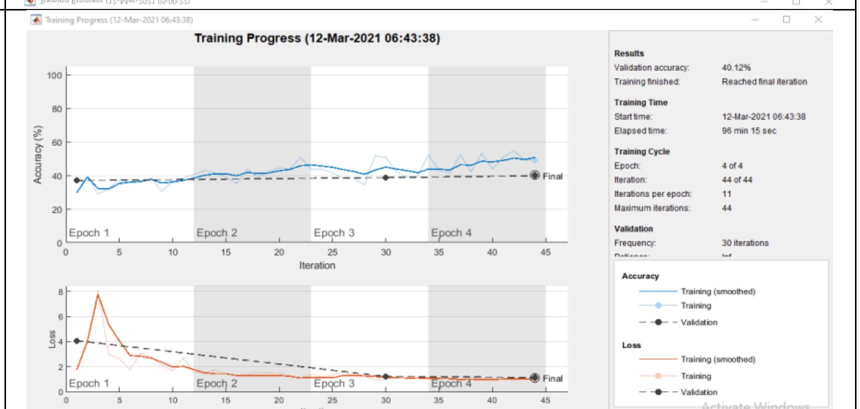
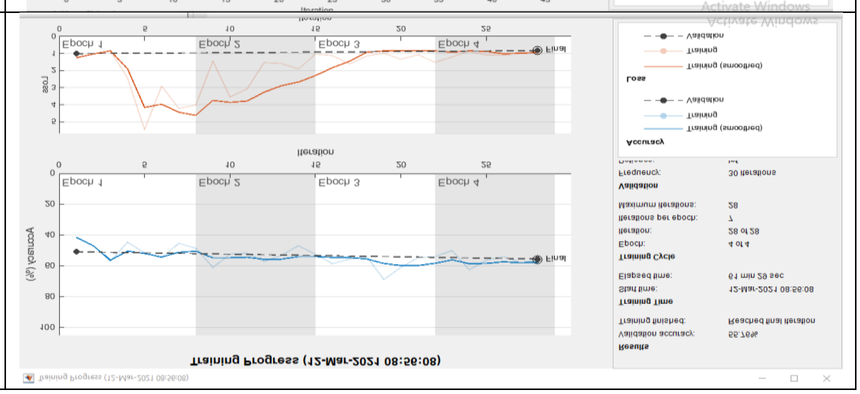
Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 9, 2025

Exp. No. 57	
Exp. No. 58	
Exp. No. 59	

Exp. No. 60	
Exp. No. 61	
Exp. No. 62	
Exp. No. 63	

Exp. No. 64	
Exp. No. 65	
Exp. No. 66	
Exp. No. 67	

Exp. No. 68	
Exp. No. 69	
Exp. No. 70	
Exp. No. 71	

Exp. No. 72	
Exp. No. 73	
Exp. No. 74	
Exp. No. 75	

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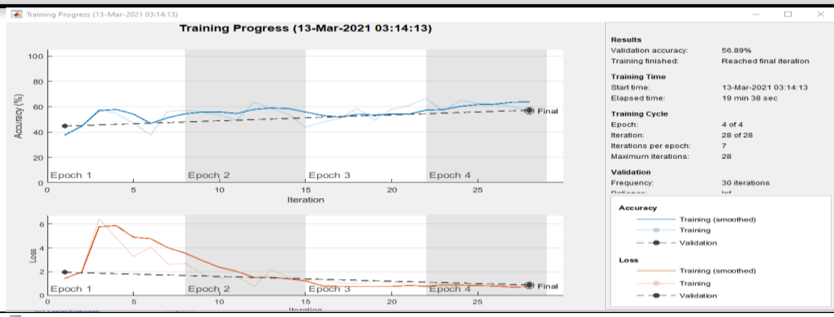
<tr><td>Exp. No. 76</td><td>
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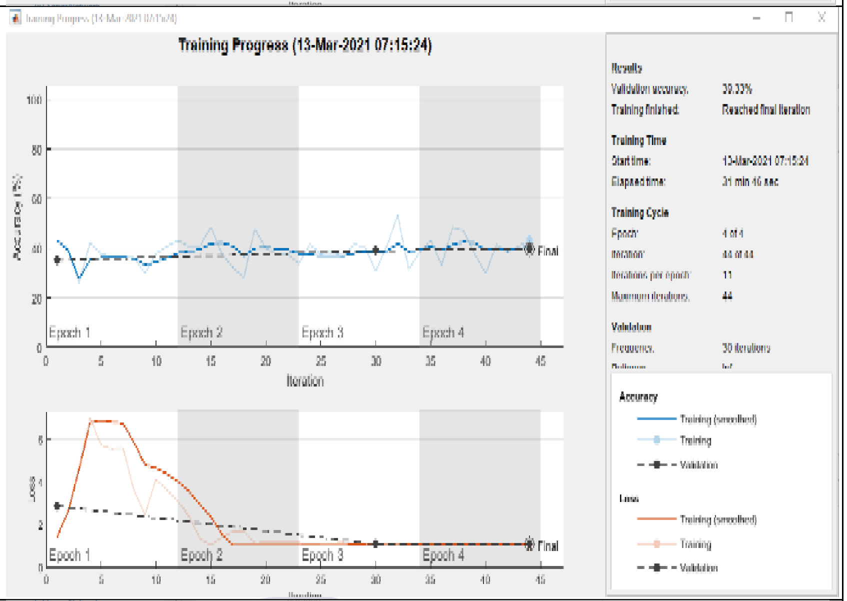
<tr><td>Exp. No. 77</td><td>
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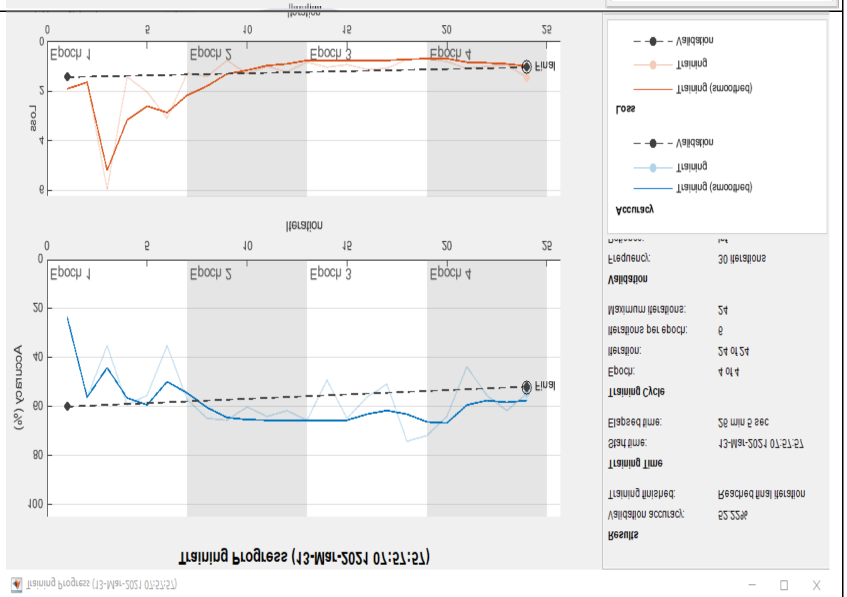
<tr><td>Exp. No. 78</td><td></td></tr>
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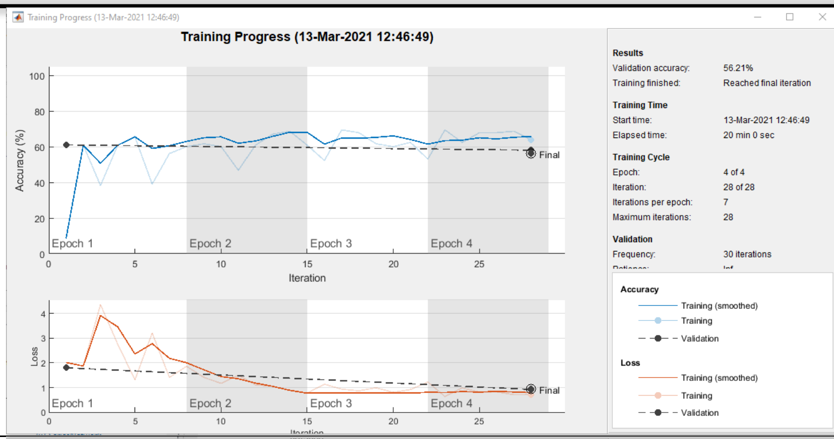
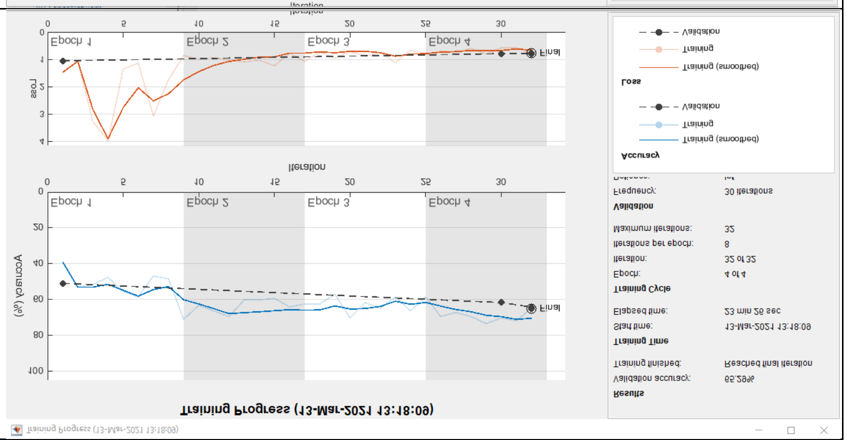
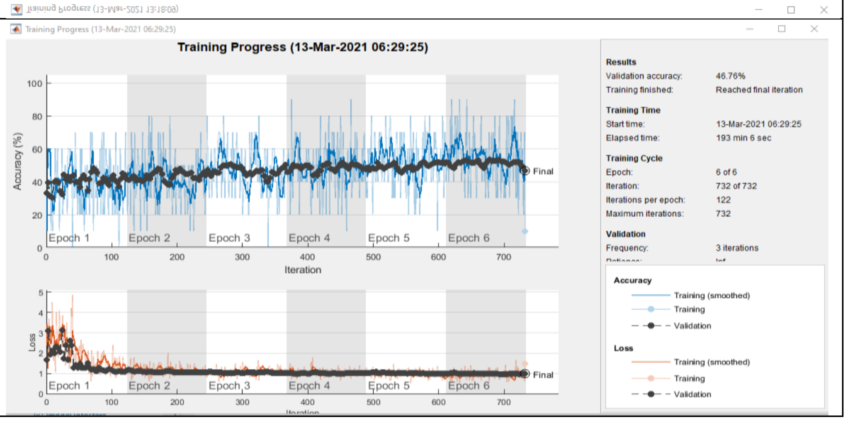
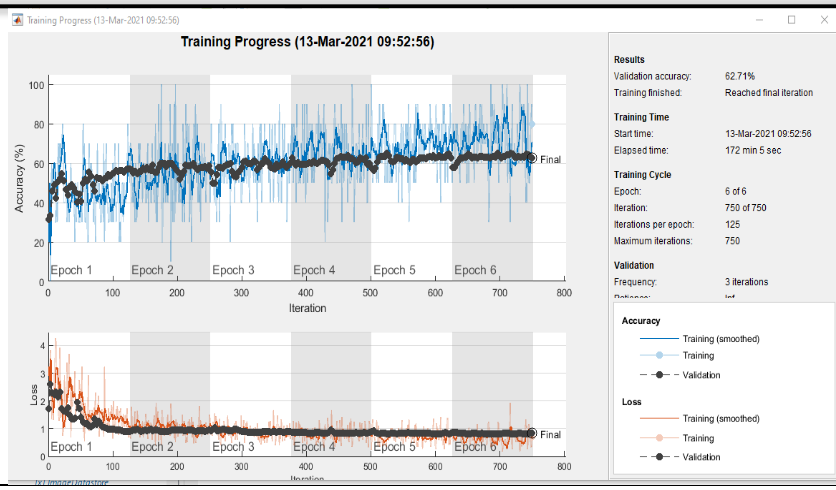
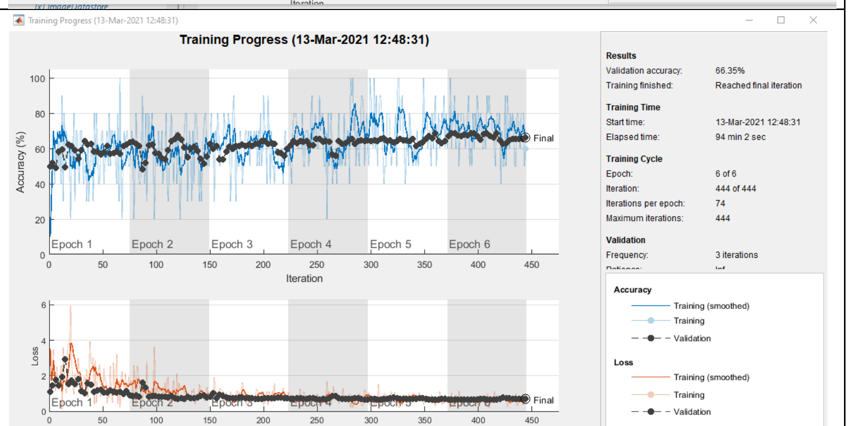
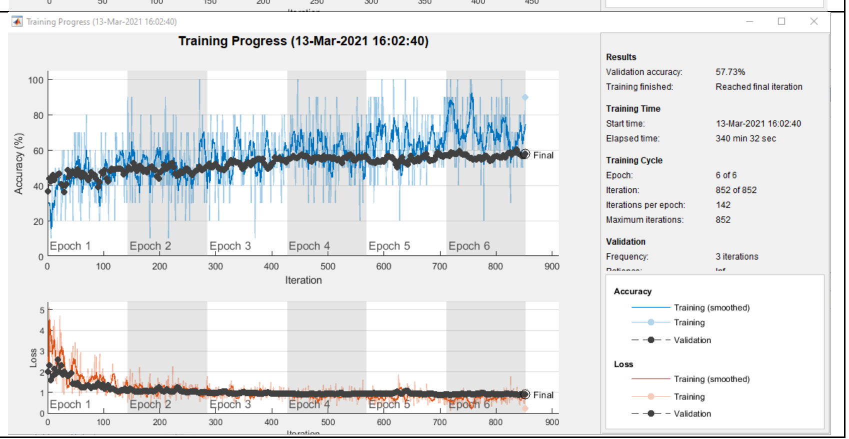
Exp. No. 79	
Exp. No. 80	
Exp. No. 81	

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 9, 2025

Exp. No. 82	
Exp. No. 83	
Exp. No. 84	

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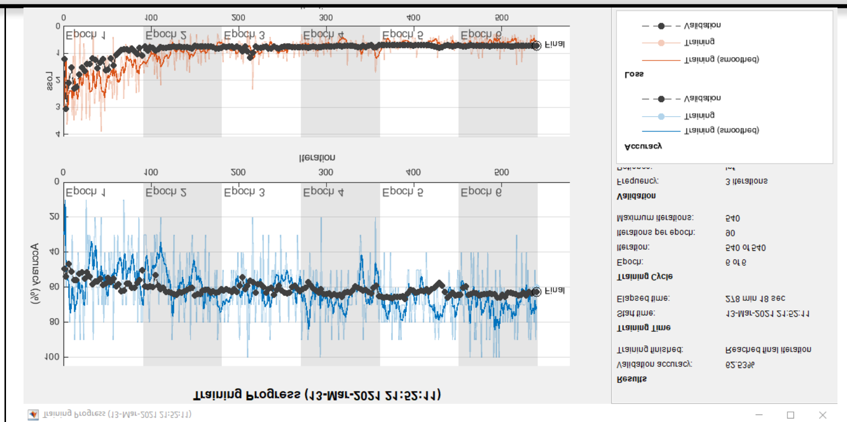
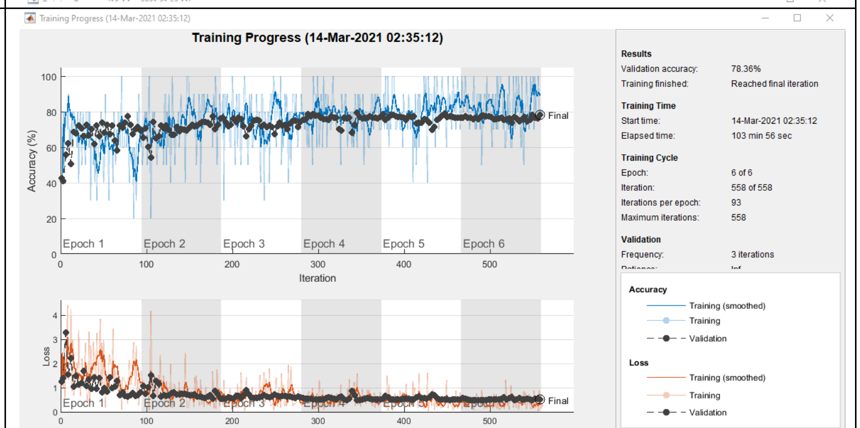
<tr><td>Exp. No. 85</td><td></td></tr>
<tr><td>Exp. No. 86</td><td>
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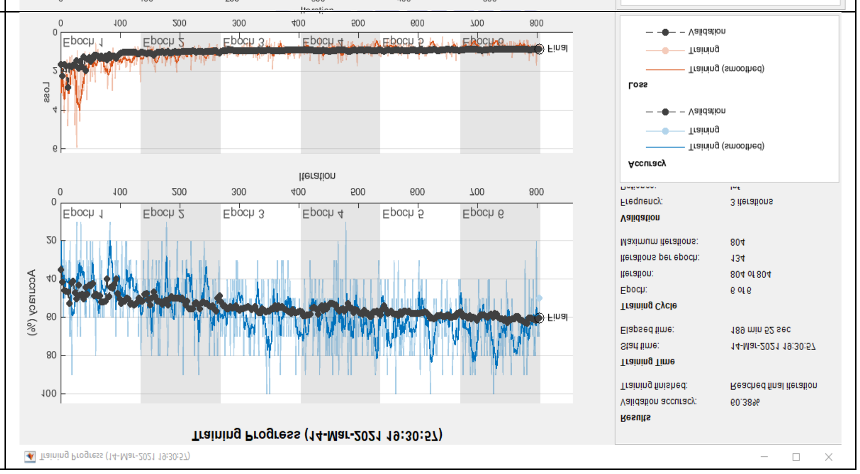
<tr><td>Exp. No. 87</td><td></td></tr>
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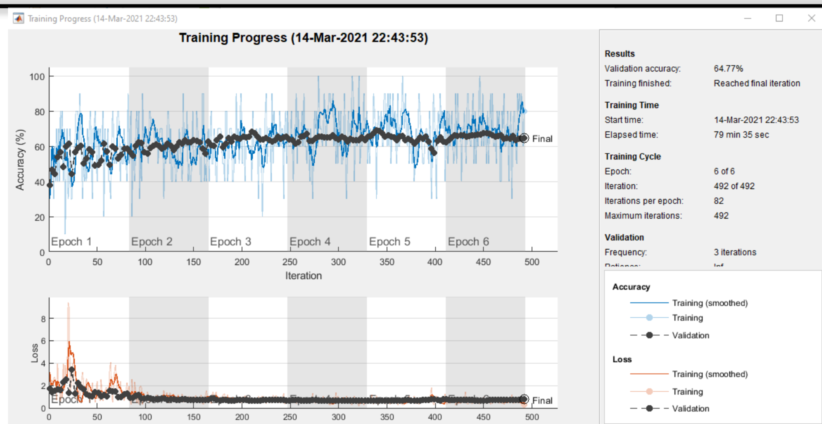
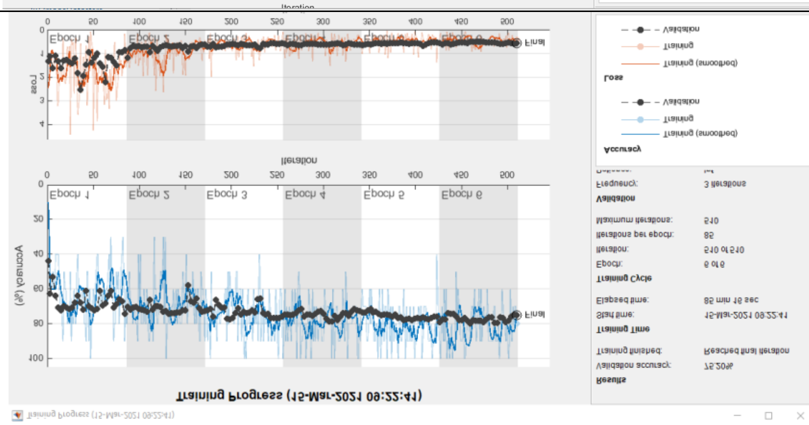
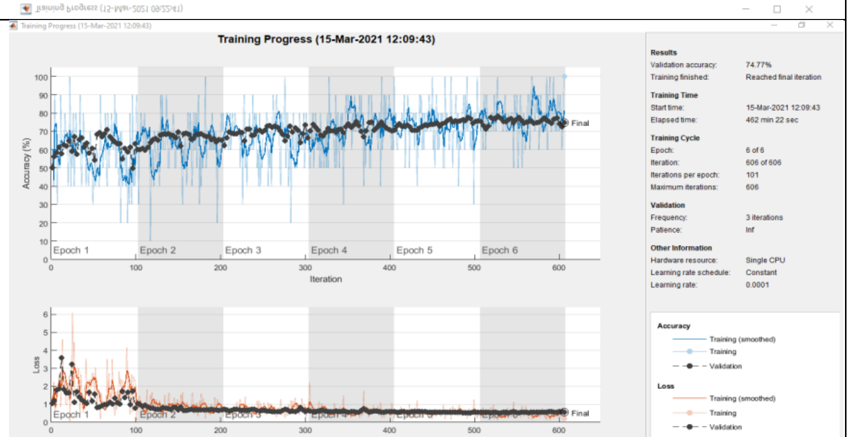
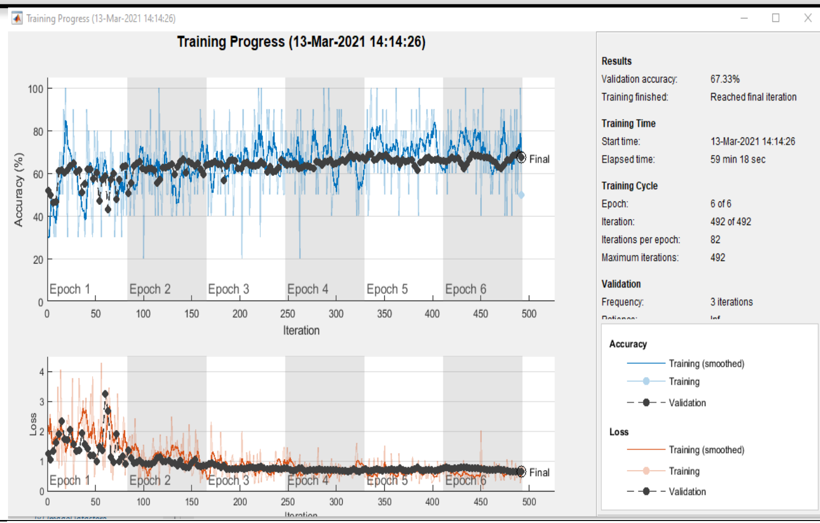
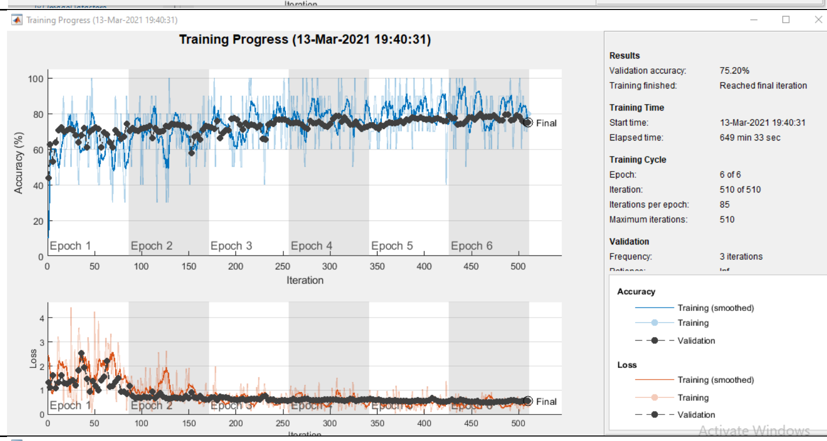
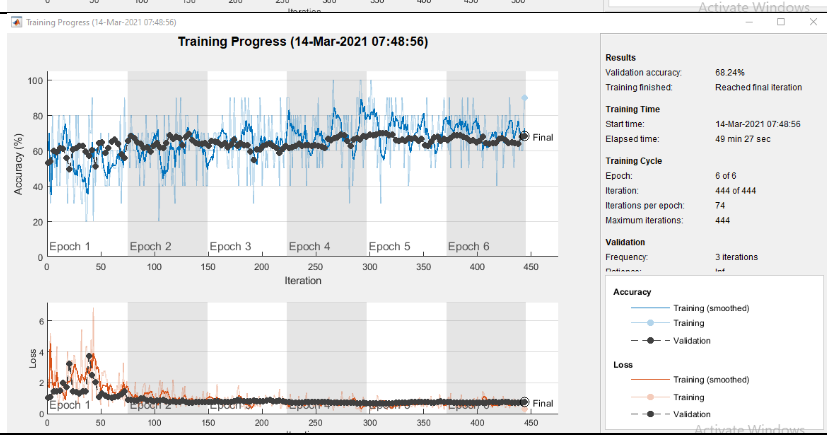
Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 9, 2025

Exp. No. 88	
Exp. No. 89	
Exp. No. 90	

Exp. No. 91	
Exp. No. 92	
Exp. No. 93	

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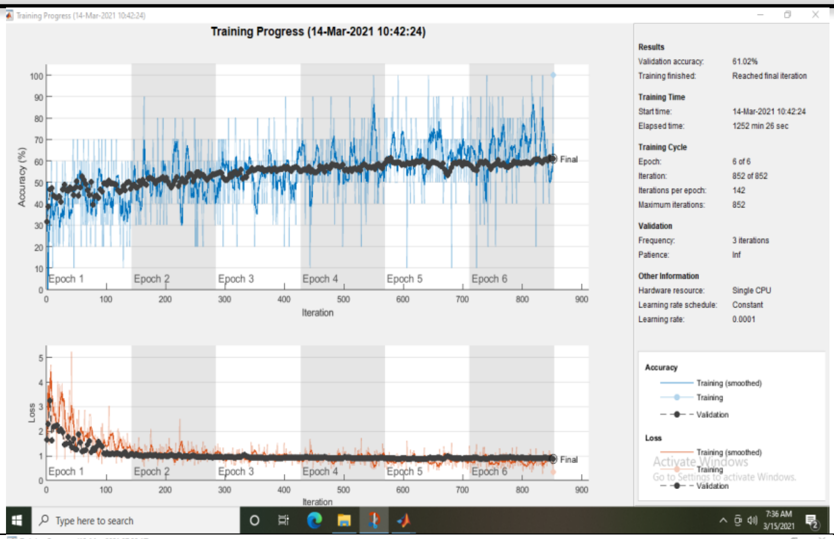
<tr><td>Exp. No. 94</td><td>
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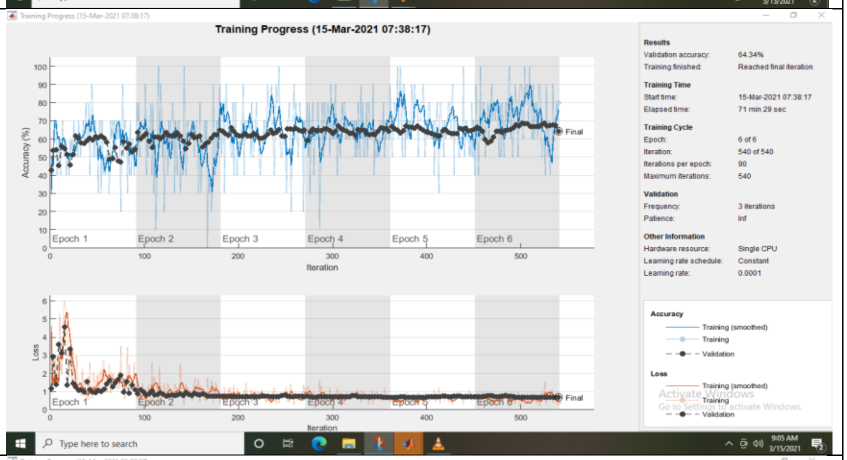
<tr><td>Exp. No. 95</td><td>
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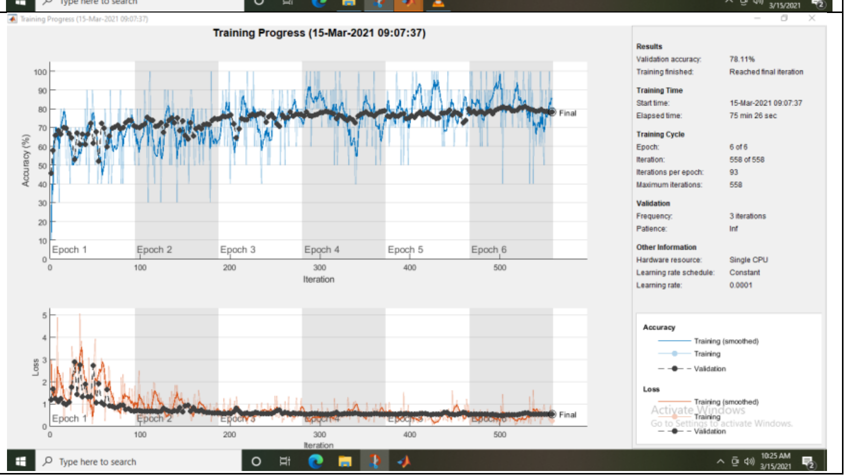
<tr><td>Exp. No. 96</td><td>
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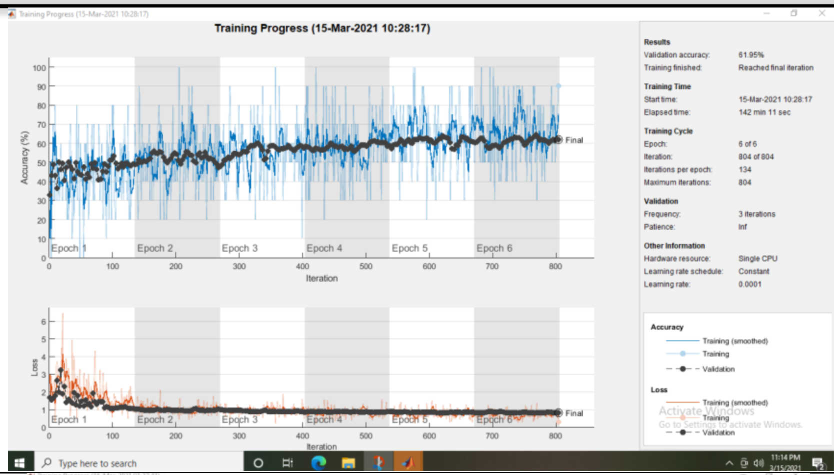
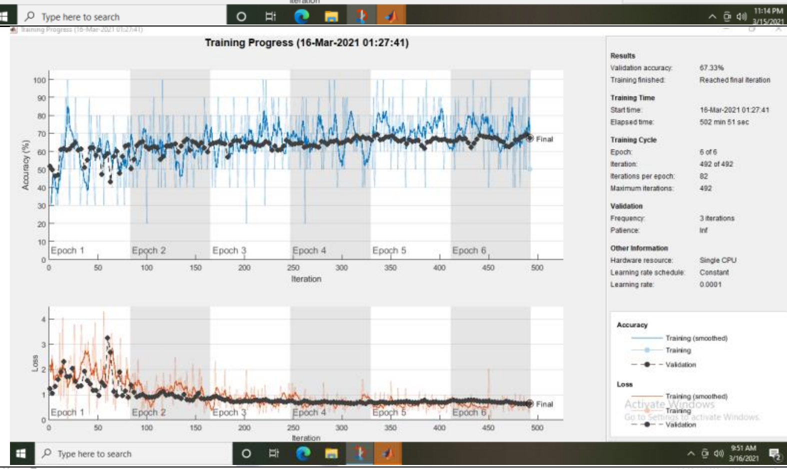
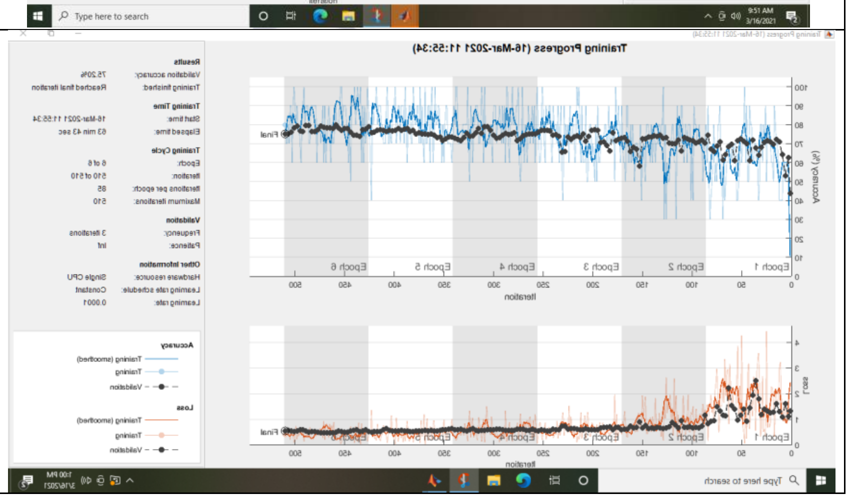
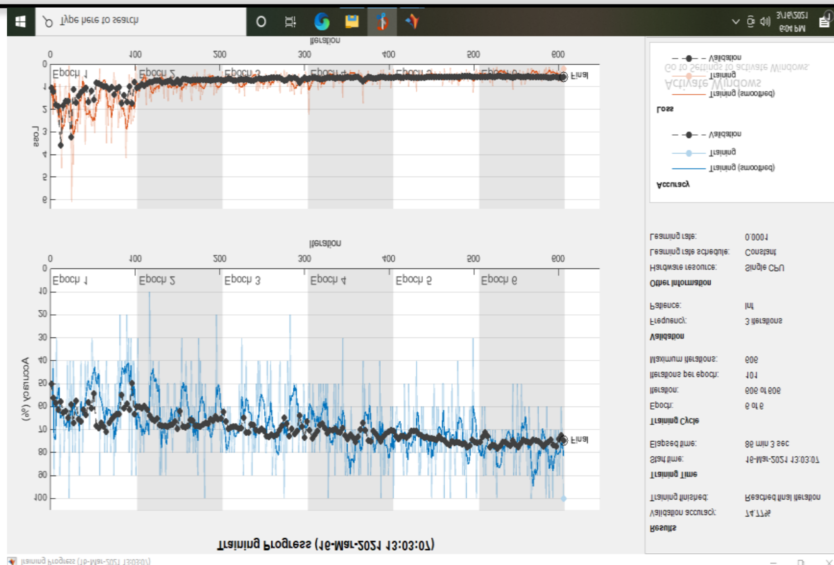
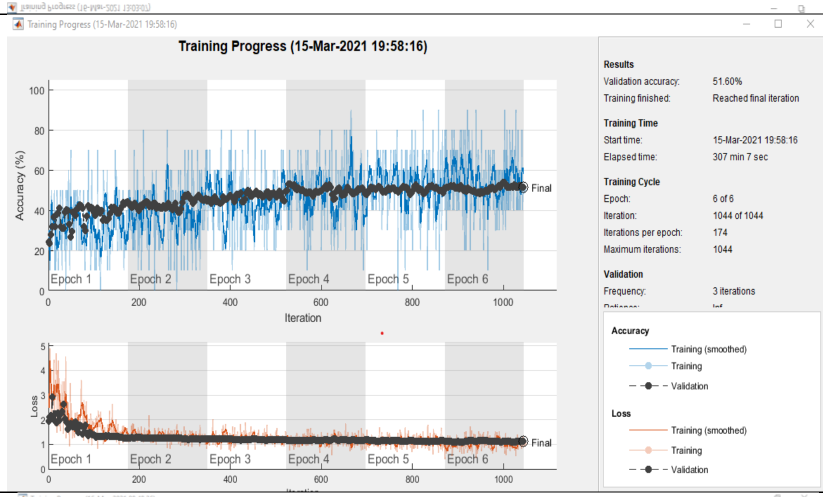
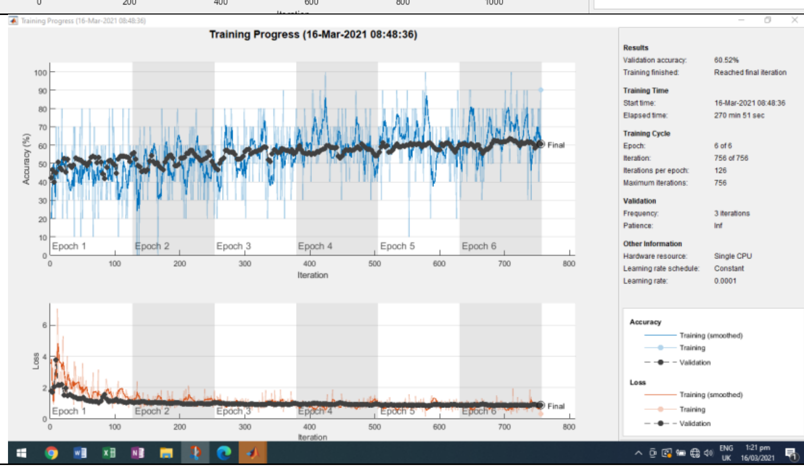
Exp. No. 97	
Exp. No. 98	
Exp. No. 99	

Exp. No. 100	
Exp. No. 101	
Exp. No. 102	

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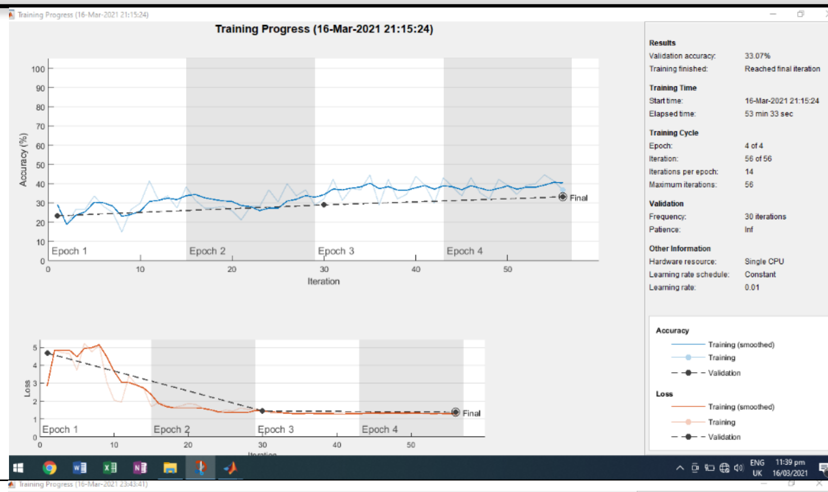
<td>
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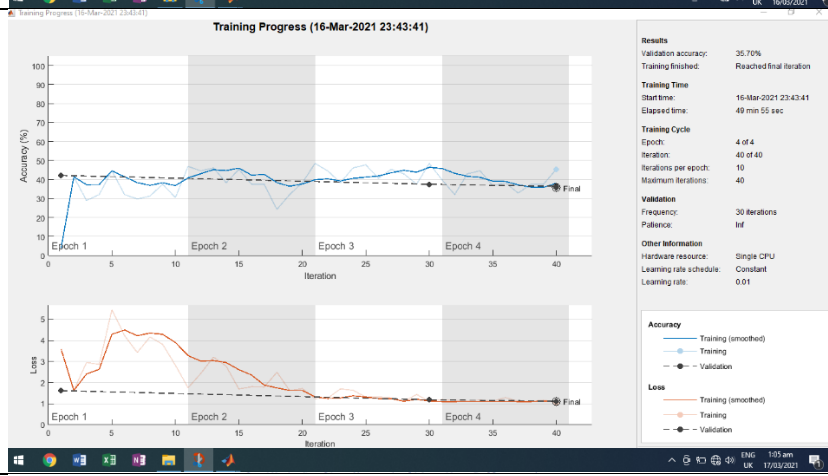
<td>
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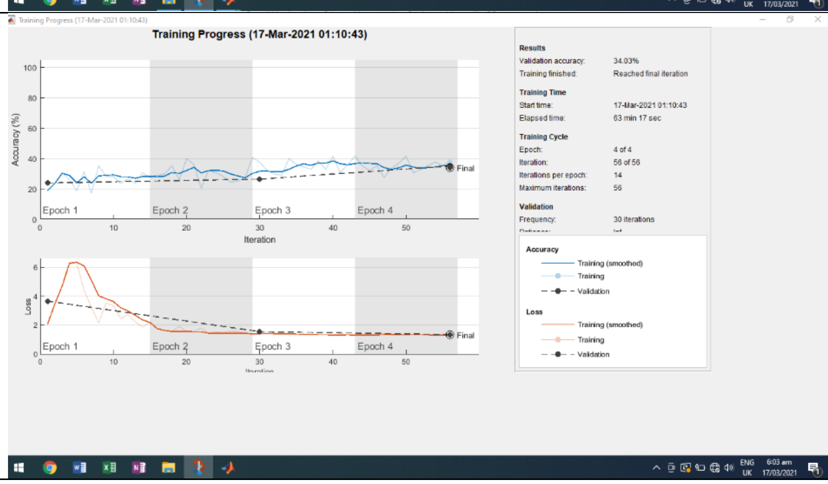
<td>
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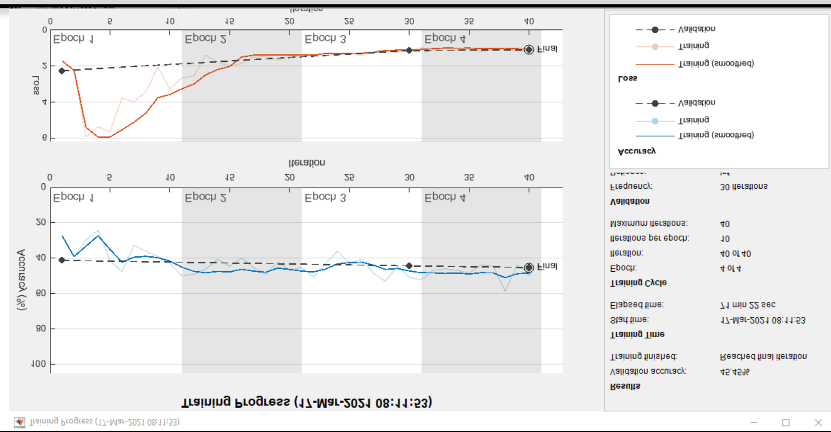

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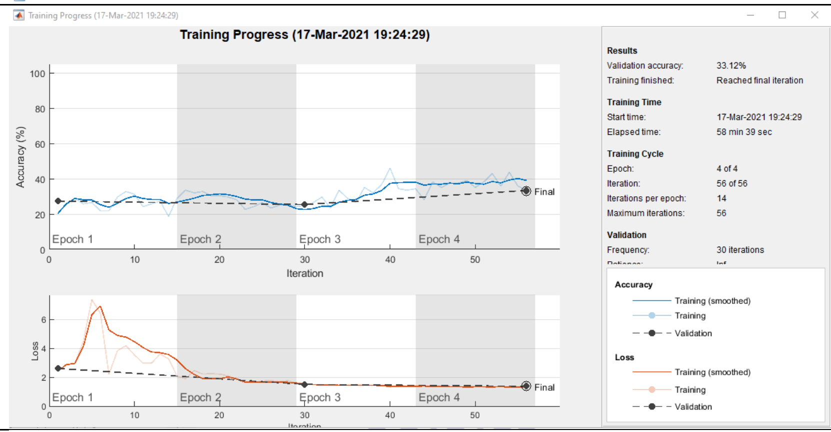

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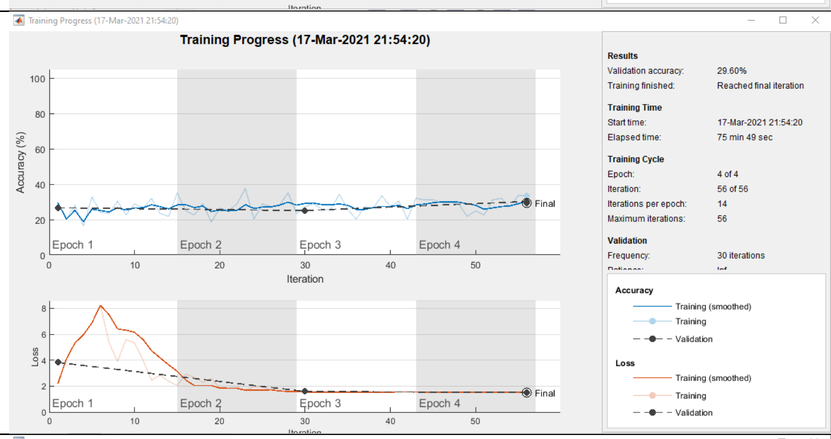

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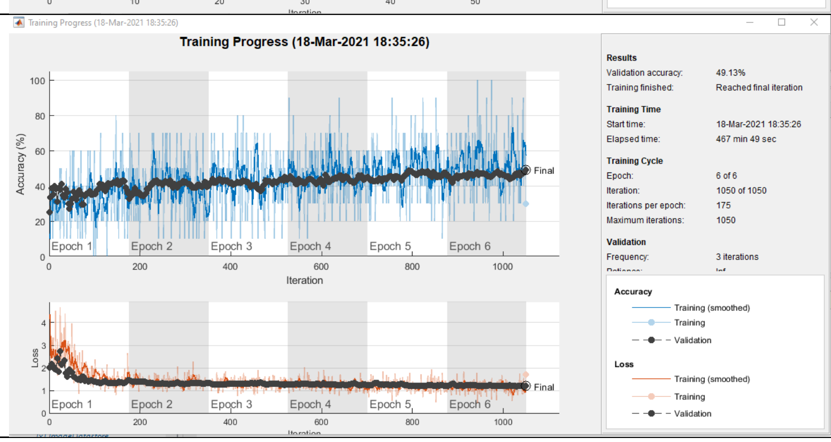

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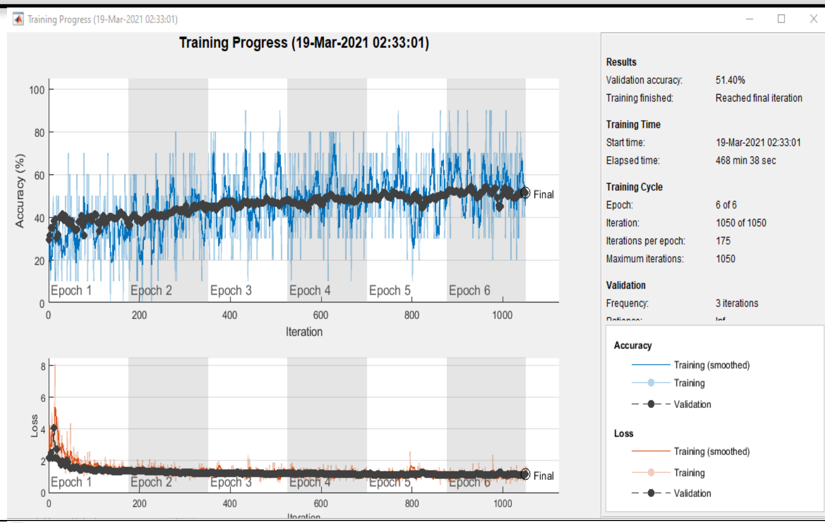
<td>
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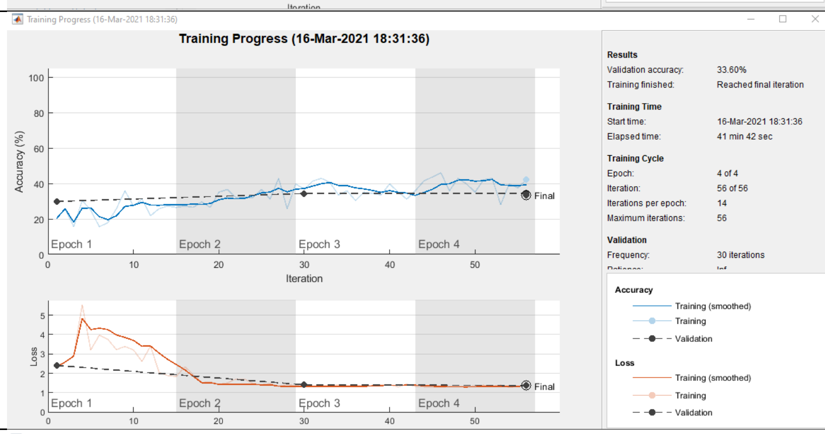
<td>
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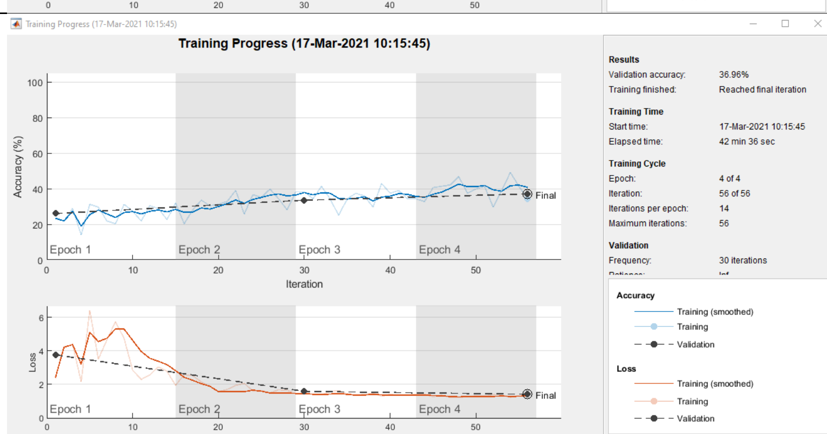
<td>
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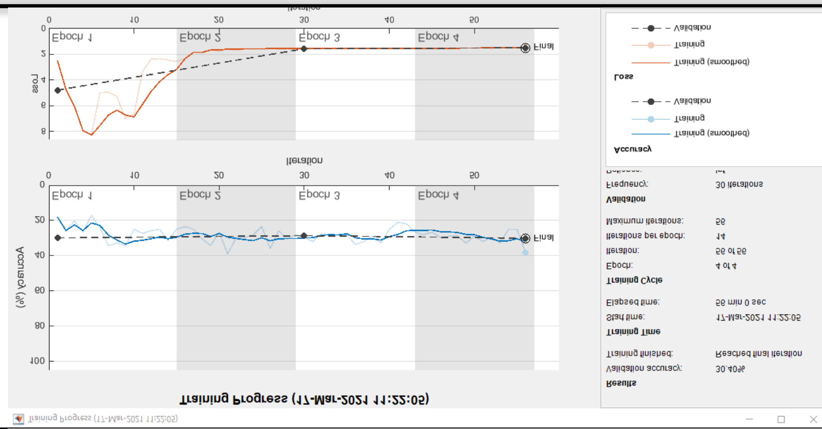
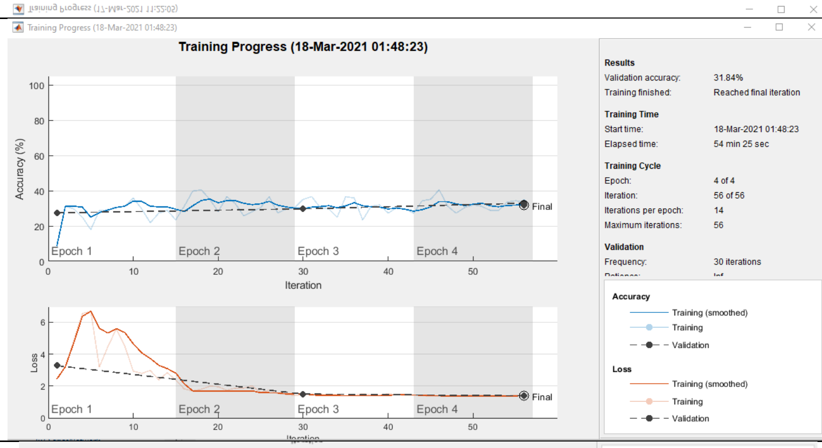
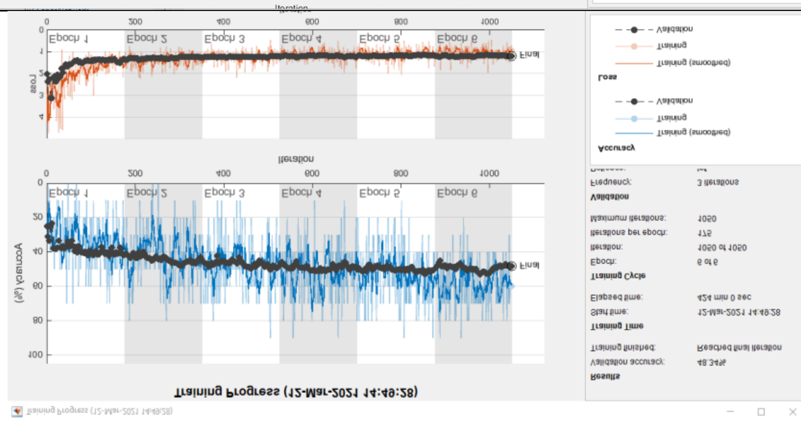
Exp. No. 113	
Exp. No. 114	
Exp. No. 115	

4.11 Discussions

Table 4.2 shows comparison of the results obtained through the proposed model with state-of-the-art methods that help to classify facial expressions. The Research activity performed by (Saha, Navarathna, Helminger, & Weber, 2018) performed experiments by using his Variational Autoencoder- Generative Adversarial Network (VAE + GAN) on local dataset and achieve 91.10% accuracy in classification of emotions. In other research, the scientist (Y. Li, Zeng, Shan, & Chen, 2018) developed a model named as Convolutional Neural Network with attention mechanism (ACNN) an tested this model with in-the-wild datasets (RAF-DB, AffectNet, SFEW) and in-the-lab datasets (CK+, MMI, Oulu-CASIA) and achieve accuracy for clear images 91.64% and 88.17% for occlusion. Similarly, Part-Based Hierarchical Bidirectional Recurrent Neural Network (PHRNN) model proposed by (K. Zhang, Huang, Du, & Wang, 2017) generates on Oulu-CASIA database,86.25% and test on MMI database give 81.18% results.

Another model named as Deep feature fusion convolutional neural networks introduced by (Tian, Zeng, McGrath, Yin, & Wang, 2019) was tested on Bosphorus dataset and achieved 79.17% accuracy for facial expression detection. (Sajjanhar, Wu, & Wen, 2018) introduced Convolutional neural networks and VGG pre-trained model and tested this model on different datasets that generated 85.19% accuracy results for (CK+), JAFFE dataset generated 65.17% results and for FACES, it generated 84.38% accuracy results. Another researcher (H. Yang, Ciftci, & Yin, 2018) developed a new method named as De-Expression Residual Learning (DeRL) and tested this with multiple datasets like Oulu-CASIA that generated 88.00% results, another dataset form MMI database generated 73.23% accuracy, BU-3DFE database produced 84.17% results and BP4D+ give 81.39% results.

Table 8 Comparison with state-of-the-art methods

Sr. No.	Author, year	The proposed methodology	Dataset used	Evaluation measures achieved
1	(Saha et al., 2018)	Variational Autoencoder-Generative Adversarial Network (VAE + GAN)	Local Data Set 237 participants	81.10%
2	(Y. Li et al., 2018)	Convolutional Neural Network with attention mechanism (ACNN)	In-the-wild datasets (RAF-DB, AffectNet, SFEW) and in-the-lab datasets (CK+, MMI, Oulu-CASIA).	Clear images 91.64% and 88.17% for occlusion.
3	(K. Zhang et al., 2017)	Part-Based Hierarchical Bidirectional Recurrent Neural Network (PHRNN)	Global Dataset from (Oulu-CASIA database, MMI database)	Oulu-CASIA database, 86.25% results. MMI database 81.18% results.
4	(Tian et al., 2019)	Deep feature fusion convolutional neural networks	Bosphorus dataset	79.17%
5	(Sajjanhar et al., 2018)	Convolutional neural networks and VGG pre-trained model	(CK+), JAFFE, FACES	(CK+) generates 85.19% JAFFE generates 65.17% FACES generate 84.38%
6	(H. Yang et al., 2018)	De-Expression Residual Learning (DeRL)	(Oulu-CASIA, MMI, BU-3DFE, BU-4DFE, BP4D and BP4D+)	Oulu-CASIA 88.00% results, MMI database generates 73.23% accuracy, BU-3DFE database produce 84.17% results and BP4D+ give 81.39% results.
7	**The Proposed Model**	**Convolutional Neural Network**	**FERG Dataset**	**97.55%**

5.1 Conclusion

In this research work, a CNN based architecture has been proposed to classify the seven basic facial expressions (Happy, Sad, Angry, Neutral, Disgust, Surprised & Fear) to predict the mood of the person. In daily life it is difficult to predict the human behavior on the basis of mood this model helps to detect the emotion accurately and can efficiently separate similar emotions.
Images are preprocessed by separating different channels like Red, Green, Blue and intensity that help to generate similar description images. Then multiple tests are performed on images, in experiment 01 only intensity channel is filter in image processing and two basic expressions are try to separate that generates 64.85% accuracy results. Similarly, experiment no 02 and 03 performed on different dataset with similar intensity channel filtration that generates 57.88% accuracy. In experiment 04 we changed the dataset with RGB and intensity channel and try to separate six expressions but due to some technical issue experiment fail to complete but according to the validation results expected about 70%. Due to accuracy, issue we repeat test with RGB and Intensity channel and achieved 50% results, in experiment 06 these results goes down, as images are not properly labeled. In experiment 07 we achieved 93.22% results with 1500 images that is reliable, we increase number of images in experiment 08 to increase the accuracy result but again due to machine error experiment fail to complete. After successfully classifying 2 expressions Happy and neutral with accuracy 93.22% we try to classify 7 expressions in experiment no 09. In experiment no. 09 we successfully classify 7 expressions and achieved 59.10% accuracy with 1400 images. In experiment 10, we increase the number of images and validation results increased to 78.43% for 7 expressions. From these experiments we can conclude that number of images had a major impact on validation results, increase in number of rich details images can increase the validation result. It has been experimentally proved that increasing the number of images has increased the achieved accuracy.

5.2 Future Work

In future work of this research work, we are able to detect facial expressions from videos and can also track a person. Head and body posters can affect the accuracy, in future we are able to detect facial expression from a crowd scenario, frontal images are not necessarily required for training and validation process. Furthermore, a well-trained model can be useful in low luminance, having ability to easily and effectively classify facial expressions in low lighting conditions.

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