Enhancing Monkeypox Diagnosis: A Machine Learning Approach for Skin Lession Classification

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

Virus which causes monkeypox is capable of infecting both humans and nonhuman primates. In order to effectively treat monkeypox and prevent the disease's further spread, it is necessary to diagnose the skin lesions caused by the disease in their earliest stages and accurately classify them. In this dissertation, we study the possibility of a system which is Machine Learning (ML) based for the classification and detection of monkeypox, a skin illness caused by the varicella-zoster virus. We acquired photos of monkeypox lesions from kaggle, augmented them in order for us to develop and test our own machine learning models. We built a basic mobile app that enables users to take images with their smartphones and then send those pictures to our machine learning models so that the pictures can be analyzed and categorized. We will update it in the future according to our users needs. Our primary objective is to examine the utility and effectiveness of applying machine learning models for the purpose of categorizing and identifying monkeypox. The possible effects of the proposed system on current healthcare systems and the usefulness of machine learning models based on a number of factors will be looked into. The goal of the study is to shed light on how machine learning models could be used in the medical field, especially in disease classification and identification. We compared ResNet50, InceptionV3, Xception model, Denesenet121 and Mobilenet. Our research results in improved accuracy, precession call and f-1 score in MobileNet and Xception Model. In order to analyse the models' output, we also discovered a confusion matrix. In Mobile net, we discovered a mean accuracy of 0.97 and a precision of 0.96. The F-1 score was 0.968, and the mean recall was 0.968. The mean precision is 0.989, the mean recall is 0.989, the mean f-1 score is 0.98 and the accuracy is 0.986 in the Xception model.

Keywords: Machine Learning(ML) ; Monkeypox; Skin disease; MobileNet; Xception Model; DenseNet; Resnet; Inception

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Chapter 1

Introduction

Our world recently emerged from the grip of the COVID-19 epidemic, while its consequences have not yet been completely mitigated. [33] [1] The COVID-19 disease outbreak, which is caused by the 2019 coronavirus, has spread all over the world.[15] [22] The cause is the SARS-CoV-2 virus, which stands for severe acute respiratory syndrome coronavirus 2. During an outbreak in Wuhan, China, in December 2019, the new virus was found. There was no way to stop the virus from spreading, so it went to other parts of China and, finally, the rest of the world. The outbreak was called a global public health emergency by the World Health Organization (WHO) on January 30, 2020, and a pandemic by the WHO on March 11, 2020. By September 13, 2022, the pandemic had caused more than 609 million illnesses and 6.51 million proven deaths, making it one of the worst in human history. [18] Though at present the situation of COVID-19 is under control, the loss the world has faced is unimaginable. Without recovering from an epidemic like COVID-19, the whole world is going to be hit by another impending pandemic today if proper measures are not taken in time. The COVID- 19 pandemic may not be over, but the world's attention has shifted to another virus: Monkeypox. Monkeypox is a contagious viral illness that can affect humans and other animals. Fever, enlarged lymph nodes, and a rash that produces blisters and then crusts over are all symptoms. [35] [30] The disease is brought on by the zoonotic monkeypox virus, a member of the genus Orthopoxvirus. The smallpox-causing variola virus is also found in this genus. Clade II (previously West African clade) produces less severe disease in humans than the Central African (Congo basin) kind. It can be passed from infected animals to humans by infected meat, bites, or scratches.

Human-to-human transmission can occur by contact with infected bodily fluids or contaminated surfaces, through minute droplets, and even via the airborne route. [17] People can transmit the virus from the time they first notice symptoms until all of the blisters have healed and fallen off, with some indications of dissemination even after the blisters have crusted for more than a week. A blister can be tested for the virus's DNA to confirm the diagnosis.An ongoing monkeypox outbreak was confirmed in May 2022. The first cluster of cases was found in the United Kingdom, where the first case—in a person with travel connections to Nigeria—was found on May 6, 2022. Monkeypox had never before spread so widely outside of Central and West Africa.Since May 18, more and more countries and areas, mostly in Europe but also in North and Africa, Asia, South America, and Oceania, have reported cases.

The Director-General of the World Health Organization (WHO), Tedros Adhanom Ghebreyesus, said on July 23 that the pandemic was a public health emergency of global importance (PHEIC). As of September 11, 2022, there were 57,669 confirmed cases in 105 countries. [1] From the recent pandemic, we have learned that, if timely action is not taken, then the Monkeypox outbreak will turn into an epidemic in no time. Early detection of this disease is the best way to stop it from turning into a pandemic. Due to similarities with chickenpox and measles, early clinical diagnosis of monkeypox is challenging. [33] When confirming PCR assays are unavailable, computer-assisted detection of monkeypox lesions may be useful for monitoring and early identification of suspected cases.

1.1 Research problem

Our study's main objective is to create a quick technique of identifying those who have monkeypox, which will allow for better surveillance and containment of the virus. To get there, we'll employ machine learning algorithms that can identify the infection in pictures. By utilizing Machine Learning (ML), healthcare systems can be improved. Machine learning (ML) is crucial when it comes to skin problems since it has the ability to increase the precision, efficiency, and effectiveness of diagnosis and therapy. There are so many important reasons why ML is important in this context, ML may be used to instruct computer algorithms to recognize patterns in photographs of skin lesions, which can then be used to automate the process of diagnosing skin disorders. In comparison to other diagnostic procedures, such as biopsies, this one can save both time and money. A More Accurate Diagnose Can Be Obtained Using Machine learning algorithms are able to detect minute changes in skin lesions that may be missed by the human eye. In the case of skin cancer, where early detection is essential to the success of therapy, this can be of great use. ML can assist dermatologists in customizing treatment plans to meet the unique requirements of each individual patient, taking into account factors such as the patient's age, skin type, and previous medical conditions. If this is the case, the treatment's results may improve, while any unintended consequences may experience a reduction. The use of ML to the examination of large datasets pertaining to skin diseases enables researchers to recognize patterns and trends that may lead to the development of new treatments. When everything is taken into consideration, machine learning has the potential to completely transform the field of dermatology by enhancing the precision, effectiveness, and individualization of the process of diagnosing and treating skin problems. Methods, tools, and uses for big data analytics were also looked into. Healthcare apps need a lot of communication and processing power, as well as conditions that make it possible to send a lot of data both inside and outside of the hospital. This was emphasized as the main reason why a networked healthcare system that gathers a lot of data is needed. AI models that use statistics to help computers learn from data without being explicitly coded are called "machine learning" models. Machine learning models have many practical applications. Despite their usefulness, good machine learning models can be challenging to build for a variety of reasons. These include the necessity for a significant volume of high-quality data, the need to choose the right algorithms, and the need to change parameters in order to achieve the desired level of accuracy.

DenseNet121, Inception V3, Xception, ResNet50 and MobileNet are just a handful of the models we have utilized to aid our investigation. We got moderate outcomes from all of them, and they were all a big help in our work. Our investigation into machine learning methods and their corresponding algorithms will prove useful in solving any issue.

1.2 Research Objectives

The monkeypox virus can spread from person to person and from primate to primate. It is essential to properly categorize and diagnose monkeypox skin lesions at an early stage in order to facilitate effective treatment and reduce the risk of illness transmission. In this thesis, We investigate whether or not monkeypox can be classified and identified using machine learning (ML), a skin condition caused by the varicella-zoster virus. We collected photos of monkeypox lesions from Kaggle. The ability of classification models that are built on machine learning to automatically sort data into many categories depending on the characteristics of those categories is one of the reasons why these models are so valuable. It is possible to increase diagnostic accuracy for a variety of illnesses, including skin disease and heart disease, by teaching classification algorithms to recognise patterns in patient data. This has a number of practical uses in a variety of contexts. The investigation and discovery of fraudulent insurance claims and financial transactions can be aided by the use of classification models. Image recognition can be used in a variety of applications and medical imaging. It is possible to train classification algorithms to recognize specific objects, people, and scenes contained inside an image. Classification algorithms are used in sentiment analysis so that the input language can be automatically categorized as either good, negative, or neutral. Sentiment analysis can be used for assessing consumer feedback or for monitoring social media. In general, machine learning classification models are helpful because they make it possible to automate the categorizing process. This is one of its primary benefits. This has the twin benefit of reducing the possibility of human error while also reducing the amount of time it takes. In addition to this, they can throw light on huge datasets, the proper analysis of which would be impossible for humans to perform without the assistance of such technologies. So we will be able to create a mobile application that will enable individuals to take pictures using their cellphones and then upload those pictures to our machine-learning models so that they may be analyzed and categorized.

Our primary objective is to conduct an investigation into the accuracy and effectiveness of machine learning models regarding the categorization and diagnosis of monkeypox. The effectiveness of machine learning models that consider a variety of different factors will be examined, as well as any potential effects the recommended approach may have on current healthcare systems. The goal of this study is to learn more about how machine learning models could be used in medicine, specifically to find and classify diseases.

In the first chapter of our paper, we introduced the topic, stated our research's goals, and discussed any relevant difficulties we encountered. In the second chapter, we provided a brief overview of the relevant literature and the algorithms, methodologies, and research output used in those papers. Along with that, we have discussed the limitations of these papers in the same chapter. In Chapter 3, we talked about our dataset and data preprocessing techniques, like- Data Augmentation. In Chapter 4, we offered a number of methods and Machine Learning models and discussed the techniques, diagrams, and equations of several ML algorithms. Accuracy, model loss, and confusion matrix analyses were performed and described in Chapter 5. Also the research studies we did was discussed in this chapter as well. Additionally, the receiver operating characteristic (ROC) curves of the models are shown, illustrating the frequencies of true positive and false positive outcomes in a binary classification model. Moreover, we had our paper-wide discussion and a brief explanation of how we created a web application that uses a picture of the user's skin lesions to determine whether they have the monkeypox or not. And finally in Chapter 6, we drew our conclusions. In the same section, we also addressed the directions we plan to take our work and the constraints we face. Finally, we included a bibliography of all the sources we consulted in the end.

Chapter 2

Literature Review

2.1 Related Works

The suggested model,[11] which is based on MobileNet V2 and the LSTM technique, has been shown to be effective for the classification and detection of skin diseases with a minimum amount of computational effort and power required. The findings are promising, as they demonstrate an accuracy rate of 85.34 percent when analyzing and contrasting the real-time photos obtained from Kaggle with alternative approaches. This indicates that the outcome will likely be successful. The architecture of MobileNet V2 was developed to be compatible with a portable device that has a stride2 procedure. The model is effective in terms of calculation, and combining it with MobileNet V2 and the LSTM module would increase forecast accuracy by keeping the information from previous timestamps. The model might be made more robust by utilizing information relevant to the present state in conjunction with weights optimization. Additionally, it is compared to several other tried-and-true models, including CNN, FTNN, and HARIS. The analysis of textured-based data has demonstrated that the suggested model exhibits superior performance in the classification of cancers and the assessment of their growth progression. The performance of the model might potentially be further enhanced by the bidirectional LSTM. It has taken a great deal of work to integrate any of the models throughout the actual construction of the suggested model. The front end was designed using Android Studio, SSDLite, and DeepLabv3+. This association was necessary in order to get the desired outcomes. Nonetheless, given the current state of affairs, there are a variety of issues that need to be addressed in the work that will be done in the future. The model's precision experienced a considerable decrease to approximately 80 percent when a collection of photographs, captured under illumination conditions that differed greatly from those employed during testing, were utilized to validate its accuracy. In the end, the suggested method is not intended to take the place of preexisting disease-diagnosis methods; rather, it is intended to augment such solutions. When it comes to accuracy, lab test results are always more reliable than evaluations that are based only on what can be seen. Also, early-stage evaluations may be hard to get right if they are only based on what the doctor can see.

The early detection of skin problems [6] is a critical step in lowering death rates and preventing the spread of disease as well as the development of skin diseases themselves. The clinical methods that are used to diagnose skin problems are both exceedingly costly and time-demanding.

The use of image processing techniques is beneficial in the early stages of developing an automated screening system for dermatology. When it comes to classifying skin disorders, the extraction of characteristics is an extremely important step.

Both the convolutional neural network (AlexNet) that has been pre-trained and the detection method developed for this study employ these two categories of neural networks. It is crucial to remember that this research is crucial for Saudi Arabia's skin problem diagnosis. This is due to Saudi Arabia's extremely hot weather, which is indicative of the prevalence of skin illnesses throughout the nation given that the country has deserts. This research contributes to the advancement of medical efficacy in Saudi Arabia.

This study built a data set [13] that mostly consisted of photos of face skin illnesses and conducted trials using five different standard CNN architectures in order to perform clinical image identification of six different prevalent facial skin diseases. The findings provide evidence that CNNs are capable of diagnosing face skin disorders. As a result of our tests, the models used to detect illnesses in various sections of the body should be distinct from one another. Furthermore, the findings of the study indicated that implementing a more coherent network architecture has the potential to enhance the efficacy of the model. The efficacy of the existing network architecture has proven satisfactory in addressing certain diseases; nonetheless, there remains scope for enhancing overall performance. As a consequence of this, particular enhancements had to be made in order for individuals to truly employ this method in their day-to-day lives in order to examine the wellness of the skin on their faces. Applying artificial intelligence methods to the practise of medicine, is not being done to its full potential, and the datasets coming from this sector need to be enhanced, both in terms of number and quality. Given the escalating quantity of facial image data related to diverse skin problems and the continuous advancement of network design, it is anticipated that convolutional neural network (CNN)-based algorithms for detecting skin diseases on the face would experience enhancement.

In this research [14], the suggested model that would enhance the categorization of skin diseases by making use of deep CNN together with a triplet loss function.

Deep learning [12], often known as DL, is a form of learning that is currently quite accurate when used in the classification of photographs. There are several potent DL architectures available and waiting to be adopted so that they may learn a new categorization issue. Because of this availability, so-called transfer learning may take place, in which other scientists do not have to construct their very own DL architecture from the ground up. They do not create a new DL architecture but rather apply the one that already exists while making certain adjustments to the specifications of the network. Here they offered the DL transfer learning adoption approach that will be employed for medical data categorization in this body of work. Learn picture data of skin illnesses with the help of the DL adoption technique, which uses DL architecture. Further patient data is included in the learning technique in the capacity of background knowledge. On applying the DL technique, they design three different kinds of learning models: transfer learning with the existing Alexnet architecture (called Alexnet-TL), Based on the findings that were obtained, one can draw the conclusion that the accuracy of the created model improves in proportion to the number of patient data that are accessible to be used as background information. Nonetheless, they have a hypothesis that the degree of accuracy needs to also be dependent on the significance of the information that is going to be provided as background knowledge. The testing of this idea is therefore the primary focus of the investigations and research moving forward.

Today, in many parts of the world [23], skin illnesses are becoming more prevalent as a direct result of prolonged exposure to the sun and variable weather. Several conditions that affect the skin need to be detected and treated as soon as possible to prevent more serious effects on the health of the people who are afflicted. Melanoma, also known as skin cancer, is widely regarded as one of the most lethal forms of skin illness. It is imperative that this condition be detected in its early stages before it has the opportunity to invade the deeper layers of the skin and begin to metastasize throughout the body. In this study, they created diagnostic algorithms for the early diagnosis of skin disorders based on artificial intelligence. In order to identify skin diseases, these algorithms were utilised to analyse images from two common datasets, namely ISIC 2018 and PH2. The photos within the two distinct data sets were categorized as follows: Twenty percent of the data was allocated for testing purposes, while the remaining eighty percent was divided equally between training and validation. The initial phase of the proposed early detection approach involved the development of ANN and FFNN algorithms.This was done to diagnose the traits that were discovered using hybrid techniques (such LBP, GLCM, and DWT), among others. Each vector (image) was altered to include 220 crucial elements that reflected the various sickness categories after the characteristics of the three different techniques were combined and compiled in a features matrix. In the second stage, CNN models based on transfer learning were applied. The models that were used were ResNet-50 and AlexNet. The performance of conventional neural networks such as Artificial Neural Networks (ANN) and Feedforward Neural Networks (FFNN) was evaluated in comparison to the outcomes obtained by ResNet-50 and AlexNet. The research findings indicated that the Artificial Neural Network (ANN) and Feedforward Neural Network (FFNN) algorithms exhibited higher performance compared to the Convolutional Neural Network (CNN) models, namely ResNet-50 and AlexNet. One of the drawbacks inherent in the study pertains to the challenge of establishing precise diagnoses, mostly attributable to the resemblance in the clinical manifestations of several diseases. There are still certain limitations and difficulties in the study despite the use of numerous optimisation approaches and the hybrid methods amongst three algorithms for feature extraction. In the future, it will be necessary to extract features using conventional techniques from a variety of algorithms, combine those features with deep feature maps that CNN models have extracted, and use two-block hybrid approaches that combine deep learning models and machine learning algorithms. CNN models are employed in the procedure's initial block to extract the deep characteristics. The results of the classification performed by the first block are used as input for the machine learning algorithm that makes up the second block, which is used to categorize dermatological conditions.
The authors of [28] worked on a cloud-based cellular network that supports remote healthcare monitoring with IoT. Machine to Machine Communication has become increasingly prevalent as a means of facilitating automated data exchange between machines, both through wired and wireless channels. The implementation of 5G

and Internet of Things (IoT) infrastructure has been initiated, along with the introduction of the Long-Term Evolution (LTE) medical gateway (LTE-MGW). This can help for reducing the network traffic load and data compression will be feasible for medical information. Moreover, the LTE-based healthcare system focuses on data transmission.It is common practise to send data from sensors that detect body temperature, blood pressure, and heart rate using NB-IoT technology. However, traffic analysis is not provided clearly so it will impact the total network load, particularly when a high number of users join at the same time

After analyzing Mohit et alTMIS .'s mutual authentication methodology, the authors of [5] presented a novel MAP(Mutual Authentication Protocol) for Telecare Medicine Information Systems (TMIS) in the cloud environment. They noted that Mohit et alprotocol.'s is susceptible to stolen-verifier attacks, a number of logged-in patient assaults, patient anonymity attacks, and impersonation attacks, in addition to failing to safeguard the session key during cryptanalysis. However, their suggested protocol offers a significantly enhanced, safe, and effective mutual authentication technique within the same setting. They used security analysis to demonstrate that their protocol offers superior security to other earlier protocols. The suggested approach is also more capable when it comes to cost computation. The researchers also conducted an analysis of formal security evaluation using a random oracle model, which ensures the preservation of all possible security properties.

Authors of [3] have made wearable ECG monitoring systems for smart healthcare. With the help of a wearable monitor, one can collect ECG signals with satisfactory accuracy. Thorough IoT cloud users can visualize their data. The Internet of Things cloud is also used to store data for later studies. Here, three different types of servers were used. As a result, data transmission latency can be minimized. Through GUI any user can access the ECG data from their mobiles. To assure privacy [9], they used authentication and key agreement (AKA), which prevents illegal access, and the Internet of Medical Things (IoMT) as an expert application that analyzes and gathers physiological data.A safe authentication approach based on the RSA and Diffie-Hellman (DH) cryptographic algorithms was developed for Wireless Sensor Networks (WSN). The suggested plan is somewhat efficient in terms of storage, connectivity, etc. Moreover, network parameters such as Throughput Transmission Rate (TTR) and End-to-End (ETE) have been evaluated using the network simulator NS3. However, this scheme could have better performance if the message transmission rate grew.

This study [27] suggested a bimodal input-based pathological voice detection. As inputs, the approach accepts voice and EGG signals. The speech and EGG signals are used as inputs to the procedure. The suggested VPD system extracts signal spectrograms and feeds them to a CNN model. This also uses the BiLSTM model. The trial findings revealed that the proposed approach was more than 95% accurate. The authors compared the proposed system to other similar systems that used the same database.

It's worth noting that the attaching of speech and EGG signals are rarely mentioned in the literature. As indicated in the table, the suggested system surpassed all other compared systems. This paper discussed using artificial intelligence in VPD systems with IoT and smart healthcare systems.

Smart healthcare is a well-studied subject. The author of this paper [26] works on the complete survey of AI and IoT for innovative healthcare. They analyze the perspective, challenges, and attributes of each research work. There is a lot of literature in the smart healthcare arena covering cloud computing at many kinds of rates and using multiple techniques.

But as far as we know, no such thorough and systematic analysis had been done before.The goal of this study was to classify and compare edge and cloud computing, AI, privacy, and security as they relate to smart healthcare in order to build a solid foundation for this new field. The question asked about how edge computing and cloud computing can work together, as well as how the IoT and IoMT can work together. It also included an assessment of IoMT device security and privacy concerns.

The author [2] works on IoT solutions going from early health monitoring frameworks in view of wearable sensors to a conversation of the ongoing fog/edge computing patterns for smart health. Information from wearable, ingestible, and implanted sensors, as well as portability and gadget use designs, can be effectively gathered and handled to uncover vital circumstances utilizing AI, Machine Learning based systems. Also, the author assisted the spread of Edge or health solutions, which use sensible enrolling ideal models to course health monitoring sensors data dealing with and storing among various centers, arranged at different levels of closeness to clients. There are two types of health monitoring issues: static remote monitoring and dynamic monitoring.

The author [41] shows that the worldwide recovery from the COVID-19 pandemic of 2022 is threatened by the MonkeyPox Virus outbreak, which killed one hundred people in three months and was designated a PHEIC by the World Health Organization. Pre-trained models like GoogLeNet, Places365-GoogLeNet, SqueezeNet, AlexNet, and ResNet-18 may be used using deep learning to identify monkeypox from images of skin lesions. After hyperparameter optimization, ResNet-18 achieved a precision of 99.49 percent. Model updates led to 95% accuracy in detecting monkeypox. Medical professionals may now make predictions thanks to LIME and GradCAM technology. GoogLeNet and Places365-GoogLeNet are portable, high-performance models used to diagnose monkeypox. ResNet-18 guarantees low-power electronics. Although they are less precise, SqueezeNet and AlexNet are nonetheless strong models. Deep learning is made possible by smartphones with superior cameras and computing power. Smartphone system-on-chip technology from Apple, Google, Qualcomm, and MediaTek speeds up the identification of monkeypox in locations lacking access to polymerase chain reaction testing. This research shows that deep learning can detect outbreaks of monkeypox throughout the world.

Author of [39] said that daily instances of monkeypox rise globally. The infectious sickness involves skin symptoms.After having great success with image-based cancer and COVID-19 diagnosis, the researchers looked into the use of Generalisation and Regularisation-based Transfer Learning techniques (GRA-TLA) for binary and multiclass classification in the diagnosis of monkeypox using Machine Learning (ML) methods. Their monkeypox diagnostic model was compared to 10 CNN models in three experiments. Their method and Extreme Inception (Xception) differentiated monkeypox patients with 77% to 88% accuracy in Studies One and Two. Study

Three found Residual Network (ResNet)-101 best for multiclass categorization at 84%–99%. Their TL method used fewer parameters and FLOPS than others, computing more efficiently. Local Interpretable Model-Agnostic Explanations (LIME) identified monkeypox onset features. The research aimed to create a TL model to detect monkeypox patients from healthy persons using a new dataset. Using TL techniques, updated Xception models may discriminate Monkeypox patients from those with other symptoms with 77% to 88% accuracy. With 84%–99% accuracy, ResNet-101 surpassed multiclass categorization. COE was computationally efficient and effective. LIME interpreted model predictions, meeting clinical trial ML model requirements. They wanted to show AI-based monkeypox diagnosis and prevention. Their freely accessible dataset will enable ML researchers without data for AI-based model building or testing. Their validated model may motivate future TL researchers. Practitioners may develop AI-based monkeypox diagnosis using TL. They may add monkeypox-infected patient images to the dataset, test the model on highly imbalanced data, and create a mobile-based diagnostic tool to overcome constraints.

The author [40] used deep learning on skin lesions to diagnose monkeypox swiftly and safely. Personalized CNN models (MobileNetV3-s, EfficientNetV2, ResNET50, Vgg19, DenseNet121, and Xception) were utilized with transfer learning and hyperparameter tuning. Deep learning for classification is demonstrated by the F1-score of 0.98, AUC of 0.99, accuracy of 0.96, and recall of 0.97 of the optimized MobileNetV3-s. Deep learning techniques for identifying skin lesions helped us combat monkeypox worldwide. Successful and low-loss CNN models with optimized hyperparameters and transfer learning. MobileNetV3-s performed best with few classified data, emphasizing the importance of clear data for image processing. Institutions of health should publish official datasets for future research. The YOLO and Detectron2 models may effectively diagnose cutaneous lesions. They demonstrate that deep learning can be used to diagnose monkeypox and that pure data and accessible datasets are necessary for advancement.

The purpose of [37] was to identify the Monkeypox virus via the use of AI-based detection approaches because of ongoing worries of a COVID-19-like pandemic. Here, fine-tuned 13 pre-trained deep learning models using universal custom layers and compared their performance on a publicly accessible dataset. The probabilistic results of the top DL models were then combined via a process of majority voting. When compared to state-of-the-art approaches, the average Precision, Recall, F1-score, and Accuracy values achieved by this ensemble strategy were 85.44, 85.47, 85.40, and 87.13 percent, respectively. The suggested strategy has proven useful for medical professionals scanning big populations. The ensemble technique showed the most effectiveness in identifying the Monkeypox virus among the DL models, with the Xception DL model coming in a close second.

According to [29], the monkeypox virus (also known as COVID-19) has recently emerged in many regions. Due to its modest transmission rate, monkeypox requires prompt diagnosis and treatment. Using deep learning, early and low-cost diagnosis is possible. In two separate research projects focusing on transfer learning, the six deep learning models VGG16, Inception-ResNetV4, ResNet50, ResNet101, MobileNetV4, and VGG19 were revised and evaluated. Based on the first evaluations, the InceptionResNetV2 and MobileNetV2 models with their enhancements yielded the highest accuracy (93%-99%). Transfer learning has recently been found to enhance disease diagnosis models in academic research. The timing of the monkeypox pandemic was explained using Local Interpretable Model-Agnostic Explanations (LIME). This study aimed to assess the performance of deep learning models in the context of asymmetric mixed data. They used Generative Adversarial Networks (GAN) to create a smartphone app for monkeypox and some fake samples. The research will be useful in developing transfer learning and explainable AI-based methods for detecting monkeypox. Researchers and doctors of the future who work on monkeypox will profit.

The research [7] focuses on the crucial field of rainfall prediction, which carries substantial consequences for disaster management, agriculture, and water resource planning. Historically, the forecast of rainfall has predominantly relied on numerical models and historical data, often encountering challenges in accurately capturing complex spatiotemporal patterns. In recent years, there has been a growing interest in the utilization of machine learning techniques due to their capacity to uncover intricate correlations within datasets. Researchers in the field of meteorology have conducted investigations into the utilization of various machine learning techniques, such as artificial neural networks and decision trees, with the aim of enhancing the precision and dependability of rainfall forecasts. Nevertheless, a significant breakthrough occurred when CNNs, initially developed for image processing, were incorporated into meteorological applications. Convolutional Neural Networks (CNNs) demonstrate exceptional proficiency in extracting distinctive features from images, rendering them highly favorable for the analysis and manipulation of satellite imagery. The primary novelty of the research conducted by Boonyuen et al. (2019) resides in the application of the Inception-V3 architecture. The architectural design, which has gained recognition for its proficiency in classifying photos, utilizes inception modules to record elements at various scales, hence improving its capacity to detect complex patterns within satellite imagery. Notwithstanding these improvements, the field encounters obstacles. The exploration of limited data availability, interpretability of complicated models, generalization over varied geographic locations, and integration of machine learning into operational meteorological systems continues to be areas of investigation. In addition, it is important to note that although machine learning has the ability to enhance prediction accuracy, the process of transforming its outputs into practical insights necessitates thorough validation and assessment of uncertainty. In summary, the study conducted by Boonyuen et al. (2019) makes a valuable contribution to the advancement of rainfall forecasting through the utilization of convolutional neural networks (CNNs), with a specific focus on the Inception-V3 architecture. This novel methodology underscores the possibility of improving short-range rainfall predictions by employing modern machine learning methodologies. As the global community continues to confront the ramifications of shifting weather patterns, the conclusions of this study have the potential to contribute to the development of more efficient catastrophe mitigation techniques and the allocation of resources.

The scholarly article [36] introduces a novel methodology for the recognition of face masks. This study seeks to respond to the increasing demand for precise and effective face mask detection in several settings, including public health and security. This study centers on the utilization of the MobileNetV2 architecture, a widely recognised CNN model, to perform the task of facial mask detection. This architectural design is renowned for its high level of efficiency and its appropriateness for real-time applications. In order to increase the performance of the system, an optimisation function is implemented with the objective of refining the MobileNetV2 model to better its accuracy in differentiating between faces that are masked and those that are not. The potential impact of the suggested system encompasses situations in which there is a need to monitor compliance with mask-wearing, such as in densely populated areas or healthcare settings. Through the utilization of sophisticated machine learning methodologies, this research makes a valuable contribution to the domain of applied artificial intelligence and computer vision. It specifically focuses on a current predicament arising from the COVID-19 outbreak and wider apprehensions regarding public safety. Potential limitations of the work may encompass the lack of diversity and size in the dataset, the selection of evaluation measures, the applicability of the model to various mask types and demographic groups, and ethical concerns pertaining to privacy and potential biases. Researchers in the field of computer vision and artificial intelligence commonly encounter many aspects that necessitate consideration when creating and evaluating recognition systems.

The author of [31] aims to present a novel methodology for the identification of COVID-19 through the analysis of X-ray images, leveraging state-of-the-art machine learning algorithms. The main aim of this research is to introduce an innovative deep neural network model that combines the Xception architecture, a widely recognized convolutional neural network, with the evolutionary algorithm. The present study introduces a novel hybrid model that has been meticulously developed to facilitate the precise and expedient identification of COVID-19 through the analysis of X-ray images. The selection of the Xception architecture is predicated upon its inherent capacity to effectively capture intricate features present within images, thereby rendering it highly suitable for the purpose of undertaking medical image analysis tasks. This integration will involve the refinement of the model's parameters with the aim of achieving greater accuracy in the differentiation of X-ray images that exhibit patterns associated with COVID-19 from those that do not. The proposed model holds significant potential implications, considering the criticality of precise and prompt COVID-19 diagnosis. If effectively implemented, this model has the potential to greatly facilitate the task of medical professionals in swiftly and accurately detecting potential cases through the analysis of X-ray images. Consequently, this technological advancement would play a crucial role in enabling early intervention and alleviating the strain on healthcare systems. In line with the conventions of scholarly discourse, it is essential to acknowledge potential limitations that may arise in the course of conducting research. These limitations encompass factors such as the accessibility and heterogeneity of the dataset employed for both train and test purposes, efficacy of the genetic algorithm in optimizing the model, and the extent to which the model can be applied to diverse populations and variations in X-ray images. In addition, it is imperative to thoroughly examine the ethical implications surrounding patient data privacy and the potential biases inherent in the dataset, as these factors warrant careful consideration.

The research paper [25] presents an application of DenseNet, a CNN architecture, for the purpose of predicting COVID-19 utilizing computed tomography (CT) pictures. The main aim of this study is to employ the DenseNet architecture, which is well-known for its dense connections and proficient feature extraction capabilities, to make predictions on COVID-19 using CT scans. CT scans have been employed as a diagnostic modality for COVID-19 owing to their ability to detect characteristic pulmonary manifestations associated with the disease. The authors wanted to develop a model with the capability to effectively discriminate between CT pictures of individuals diagnosed with COVID-19 and those who were not. The potential significance of this work is substantial, given the importance of precise and timely identification of COVID-19 for effective patient care and public health interventions. The application of a high-performing model that utilizes CT images has the potential to improve the efficiency and accuracy of medical practitioners in diagnosing patients. Possible drawbacks to the study may encompass the dimensions and inclusiveness of the dataset employed for training and evaluating the DenseNet model, along with the prospective difficulties in extrapolating the model's efficacy to diverse populations, variances in CT scan precision, and potential data biases. The ethical problems pertaining to the privacy of patient data and the interpretability of the model's judgements are crucial factors that require attention and resolution. The paper's primary emphasis on the utilization of deep learning techniques in medical diagnosis is in accordance with the prevailing inclination of employing artificial intelligence in addressing healthcare complexities. Nevertheless, it is imperative to thoroughly examine the methodology, results, and limitations of the research by directly referring to the original work.

The study [19] centers on the application of the RESNET architecture to the job of image classification. The main objective of this study is to employ the RESNET architecture, a deep convolutional neural network (CNN) framework widely recognized for its effectiveness in handling the challenges related to training very intricate networks, in order to perform image classification. The adoption of RESNET has been extensive in diverse computer vision tasks owing to its capacity to address the issue of disappearing gradients and facilitate the training of deeper models. The significance of this study presumably resides in the utilization of the RESNET framework for the purpose of image classification, which is considered a key undertaking in the field of computer vision. The study showcased the effectiveness of the proposed architecture in obtaining precise and efficient image categorization. By doing so, this research contributes to the advancement of the fields of image analysis and machine learning. The exact dataset utilized for the study's training and testing of the RESNET model, the selection of hyperparameters, and the degree to which the model's efficacy is evaluated in comparison to other cutting-edge image classification techniques are potential sources of bias. Furthermore, although RESNET is a robust architectural model, its implementation may provide computational difficulties because of its extensive depth, which may not be thoroughly addressed in the abstract.

Table 2.1: Assessments of dataset durning study

Ref.	Task	Classifier	Database	Accuracy
[1]	B5G combined with COVID-19 vertical training	CNN	COVID-19 Dataset	88.79%
[2]	Medical Signal, AI, Edge	LSTM, CNN	N/A	NAS
[3]	Smart Health Monitor	Cryptography,data encryption, genetic algorithms	N/A	N/A
[4]	Disease Prediction	Decision Tree, Naive Bayes, Nearest Neighbor	Various ECG data	Decision Tree= 95% Nearest Neighbor= 95% Naive nBayes= 94%
[5]	Security preservation	N/A	N/A	N/A
[6]	Surveyed ML and DL algorithms used in IoMT for the betterment of healthcare	Linear Regression, KNN, CNN	N/A	LR= 97.8% CNN= 90% 96% KNN= 80.90% - 83.76%
[7]	Data Accessing method	EES, EEE, SOA, MDA	Different hospitals, Cloud Application	N/A
[8]	IoT- Architecture	Various ML and AI algorithms	N/A	N/A
[9]	Cloud-based cellular networking System to support healthcare monitoring	N/A	Oxygen saturation variability	N/A
[10]	Security and privacy preservation	N/A	Various kinds of data	N/A

[11]	ECG monitor system	N/A	N/A	R waves 0.68s, QT is 0.32s .
[12]	Privacy Preservation Protocol	N/A	N/A	N/A
[13]	Voice pathology system	CNN, LSTM	SPD database	CNN = 95%Voice 94% EEG=93.71% Fusion=95.65%
[14]	Health monitoring	J48Graft decision tree, s(SVM) and random forest(RF),Naive Bayes, k-Nearest Neighbors, and classification/regression trees	Cloud Application	N/A
[15]	Skin Disease	Mobilenet V2 with LSTM	N/A	Mobilenet = 85.34%
[16]	Skin Image Classification	CNN	N/A	100%
[17]	skin lesion	Inception-ResNet-v2	N/A	54.1%
[18]	ChickenPox	Inception-ResNet-v2, ResNet152	N/A	Inception-ResNet-v2 = 87.42% , ResNet152 = 84.91%
[19]	Skin Disease and lesion	Alexnet-TL, FESVM	N/A	Alexnet-TL = 79.29 %, FESVM = 78.70%
[20]	Skin disease detection	ResNet-50, AlexNet	ANN	ResNet-50 = 90%, AlexNet = 95.3%

According to the above summary table of our literature analysis and other studies, there are many studies where data is collected from various hospitals and cloud systems. Therefore skin data has been collected by Kaggle and other general databases. Some of the image data come from health monitoring apps, others had private sets. Most of the situations they employ machine learning models like CNN, AlexNet, ResnetV2, Resnet152, LSTM, and other general CNN methods. As a result, the suggested methodology's accuracy ranges between 75% and 100%. Those with high accuracy and f1-scores appear to have skewed datasets. From our hypothesis, we may predict that the data preparation and data augmentation are not good at all for the investigations.

Researchers place a premium on data pre-processing, data augmentation, and data standardization in our research. Normalization reduces duplication and redundancy by evaluating the picture data types represented in the collection. It is advantageous to divide a large database table into smaller tables and connect them using relationships. In our research, we not only focus on high accuracy, but we also investigate our algorithms by creating a confusion matrix with multiple folds. Evaluating the comparison between algorithms and approaches increases the interoperability and distinctiveness of our research.

Chapter 3

Dataset

3.1 Descripion of Data

We used a dataset that is available in Kaggle had been used in this research. During the course of our study project, we segmented our dataset into three distinct portions or datasets. Images of monkeypox are included in the initial portion of our dataset. In the second section, there are visual representations of measles and chickenpox. The final section of our data collection consists of pictures of people with normal skin. We utilised picture augmentation strategies like- rotation, shearing, scaling to expand the size of our dataset and better train our model. We currently have a dataset consisting of 1262 photos of different classes and 1705 images of monkeypox. We have cut the dataset in half so that we can prepare and test it. The testing dataset contains the remaining 20% of the all-out photographs, whereas the training dataset has around 80% of the all-out pictures.

Table 3.1: Train and test set

Label	Train Set	Test Set
Monkey Pox	837	279
Chicken Pox and Measles	594	198
Normal Skin	879	293

Figure 3.1: MonkeyPox and Others images

3.2 Data preprocessing

Starting with data preparation and building an embedding layer for machine learning models, the proposed approach is described. After collecting data, data cleaning is very important for image datasets. It is really very challenging to classify some of the diseases because MonkeyPox and ChickenPox images have some close pictures. Data preprocessing improves accuracy and reliability. Eliminating missing or inconsistent data values due to human or machine mistake is one way in which preprocessing can increase the accuracy and reliability of a dataset. It guarantees data consistency.

The goal of pre-processing is to improve the image data by getting rid of unwanted distortions or bringing out image features that are important for further processing, even though geometric transformations of images, like rotation, scaling, and translation, are included here because they are similar to pre-processing methods.

Data augmentation: The practice of enhancing data entails making a few small changes to already-existing data in order to broaden its variety without gathering new data. A dataset can be expanded using this method. A neural network can be kept from identifying unrelated characteristics with the use of data augmentation. The model thus operates more effectively. Various strategies can be employed to enhance data, such as horizontal and vertical flipping, rotation, cropping, shearing, and other similar methods.

In the case of monkeypox, chickenpox, measles and normal skin image datasets, The diversity was improved through the use of data augmentation and variability of the image data through preprocessing. Various image enhancement techniques were used to produce enhanced versions of the original images. This involved horizontally and vertically flipping the images, randomly cropping smaller regions, rotating the images at different angles, scaling and resizing them to different dimensions, adjusting brightness and contrast levels, adding random noise to simulate real-world flaws, jittering the colour channels, and translating the images by shifting them in different directions. By implementing these transformations, a larger and more diverse dataset was produced, with variations in object orientation, size, lighting conditions, noise, colour, and object position within the images. This augmented dataset provided the model with a broader range of examples from which to learn, allowing it to generalise better to new and unseen monkeypox, chickenpox, measles and normal skin images and become more robust in its ability to accurately detect and classify the disease.

Table 3.2: Parameters for online data augmentation

Rescale	1/255
Width shift	0.1
Height shift	0.1
Horizontal flip	False
Vertical flip	True
Optimizer	Adam
Batch size	16
Learning rate	0.0001

Chapter 4

Proposed Methodology

4.1 Work Flow

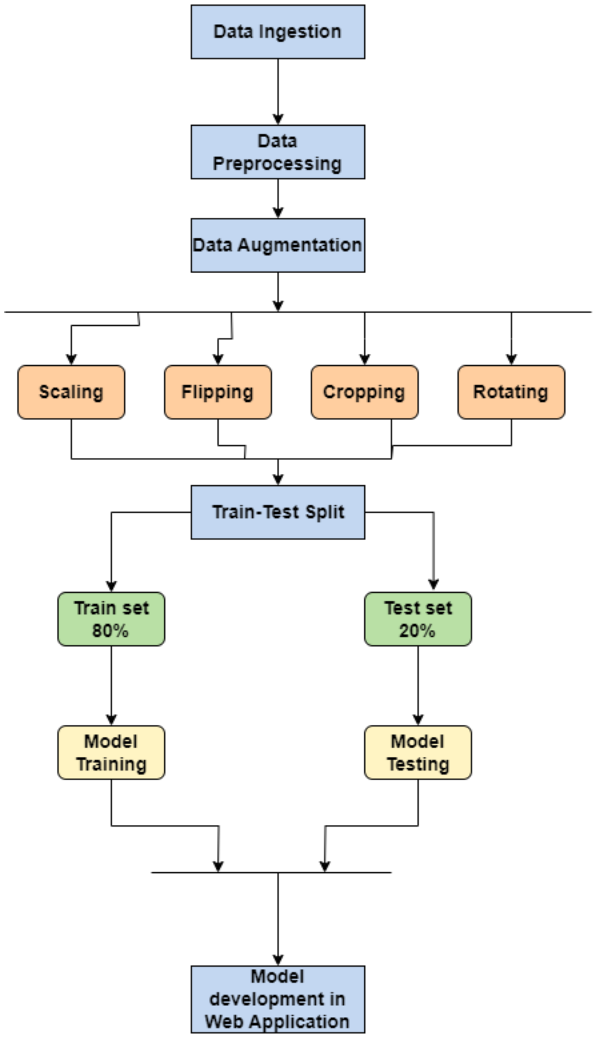

Figure 4.1: Work Flow of the research

We start with Data Ingestion, which is the process of collecting the data needed for training the model. Now the raw data is processed to be used in a machine learning model. This includes: Scaling: Adjust the scale of the data to a standard range, usually 0-1. Flipping: Change the orientation of images or other data, if applicable. Cropping: Reduce the size of images or other data, if applicable. Rotating: Rotate images or other data, if applicable. After preprocessing, the data is split into two sets: the training set (80% of the data) and the test set (20% of the remaining data). By using the training set to teach the model to make predictions or classifications, the training data is trained to generate the model. Next, the test set is used to assess how well the model has learned from the training phase. This offers a measurement of the model's performance on data that has not yet been observed. After the training is complete, the model is archived so that it can be used at a later time.
Finally, the saved model is used in the development of a web application. This involves writing backend code to load and use the model, designing a user interface to interact with it.

4.2 Machine learning Model Description

Based on skin images gathered by image sensors employing IoT devices, the recommended model applies some image classification techniques to identify the monkeypox disease. Machine learning is projected to aid physicians in reaching a more accurate diagnosis by offering a quantitative study of lesions. [4] [8] [16] Additionally, it might hasten the clinical process.

A. Inception V3: Convolutions neural networks, or Inception V3, are one such class. There are several convolutions layers and max pooling layers in it. It also comprises neural networks that are fully coupled. You don't need to memorize its structure, though. Instead of us, Keras would take care of it. This renowned architecture, which is a member of the Inception family, was developed in 2015 and demonstrated approximately 78.1% accuracy on the Image Net data set. The network features batch normalization, max and average pooling, dropout layers, and symmetric and asymmetric blocks of convolution.

The total loss used by the inception net during training.

$$\text{Total loss} = \text{real loss} + 0.3 \times \text{aux loss 1} + 0.3 \times \text{aux loss 2} \tag{4.1}$$

The above equation shows a loss function that is used in both machine learning and deep learning. "Total Loss" is the main goal that needs to be reduced as much as possible during training. "Real Loss" is the main loss function for the main job. "Auxiliary Loss 1" and "Auxiliary Loss 2" are additional loss terms that are meant to capture specific data characteristics or regularization effects. The "0.3" in front of each of the two secondary losses shows how important they are, since each of them makes up 30% of the total loss. This way of putting things makes it possible to find a balance between optimizing the main job and taking into account the other goals, which are represented by the auxiliary losses. By changing these weights, you can change how much weight the model gives to different parts of the training data.

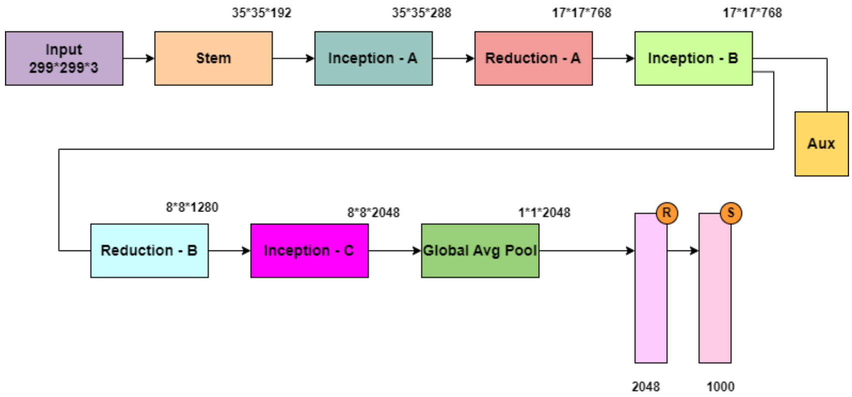

Figure 4.2: Architecture of Inceptionv3 Model
[44]

B. DenseNet Model: In contrast to prevailing assumptions, DenseNets exhibit a reduced parameter requirement compared to ordinary convolutional neural networks (CNNs) due to the elimination of the need to learn duplicate feature maps. [8] Additionally, it has been demonstrated by numerous ResNets versions that many layers may be eliminated because they are seldom contributing. Because each layer contains weights that must be learnt, ResNets really have a lot of parameters. Instead, DenseNets layers are incredibly narrow (e.g., 12 filters) and only provide a fefw number of new feature maps. Because of information flow and gradients, it is also hard to train networks that are very deep. The utilization of DenseNets can effectively address this issue, as each layer within the network possesses direct access to both the gradients originating from the loss function and the source image.

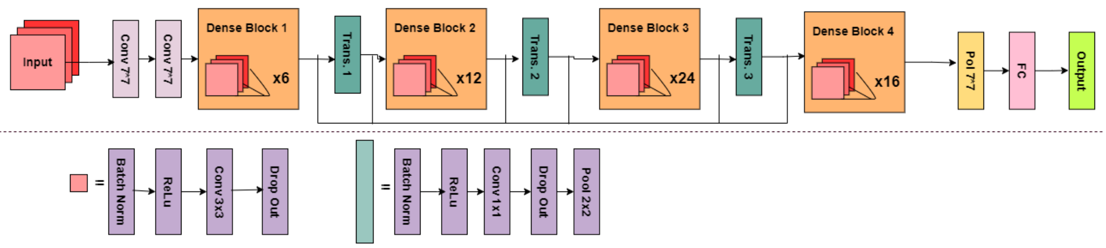

Figure 4.3: Architecture of DenseNet Model
[43]

C. Xception Model:
The present model represents a significant modification of Google's Inception network from the year 2017. The main objective of the Xception architecture is to enhance the efficiency of the Convolutions operation within Inception blocks. The achievement was attained through the utilization of a modified depth-wise separable convolution technique, which entails the sequential execution of pointwise and depth-wise convolutions. In this particular instance, the spatial convolution that operates on each channel individually is denoted as the depthwise convolution, which results in a modification of the dimension.The Xception CNN consists of a total of 71 layers. The ImageNet database encompasses a pre-trained neural network that has undergone training using a dataset including more than one million photographs.

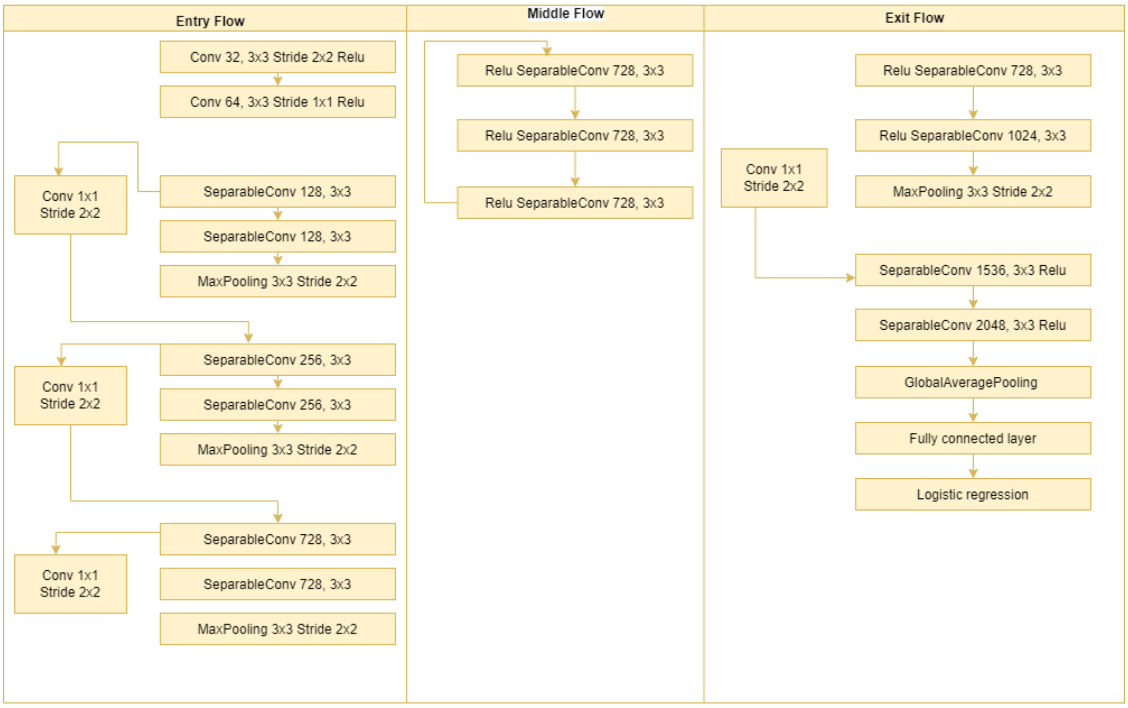

Figure 4.4: Xception Model Architecture.
[32]

A depthwise separable convolution layer system constitutes the complete architecture of an Xception model. The main premise is that spatial and cross-channel correlations may be entirely separated during mapping.

The feature extraction base of the network is made up of 36 convolutional layers spread across 14 modules. All but the first and last modules are surrounded by linear residue blocks.

D. MobileNet: MobileNet is an ultra-lightweight convolutional neural network (CNN) model architecture that was developed primarily for mobile and embedded devices that have restricted access to computing resources. [10] The underlying technique of MobileNet is built on depthwise separable convolutions, which are the main building block of the network. [10] The pointwise convolution mixes the output channels of the depthwise convolution with numerous 1x1 convolutions, as opposed to the depthwise convolution, which applies a single convolutional filter to each input channel. Because it cuts down on the number of parameters and processes, this strategy brings the total computing cost down by a substantial amount. In most cases, MobileNet models are pre-trained on large-scale picture datasets like ImageNet. However, in addition to the initial MobileNet design, a number of pre-trained variations have been created in order to establish a balance between the level of accuracy and the size of the model. For instance, MobileNetV2 is an improvement over the first version of MobileNet. [21][42] This is accomplished by incorporating inverted residual blocks and linear bottleneck layers. The end result is improved performance despite the model size being the same. The design is improved even more with the introduction of squeeze-and-excitation blocks as well as additional optimisations in MobileNetV3. MobileNet models have shown to have exceptional performance on mobile and embedded devices, which enables real-time inference and deployment on platforms with limited resources. [10] [21] [38] Because it makes it possible to deploy deep learning models on devices with limited resources in an effective manner, MobileNet has made a significant contribution to the area of computer vision.

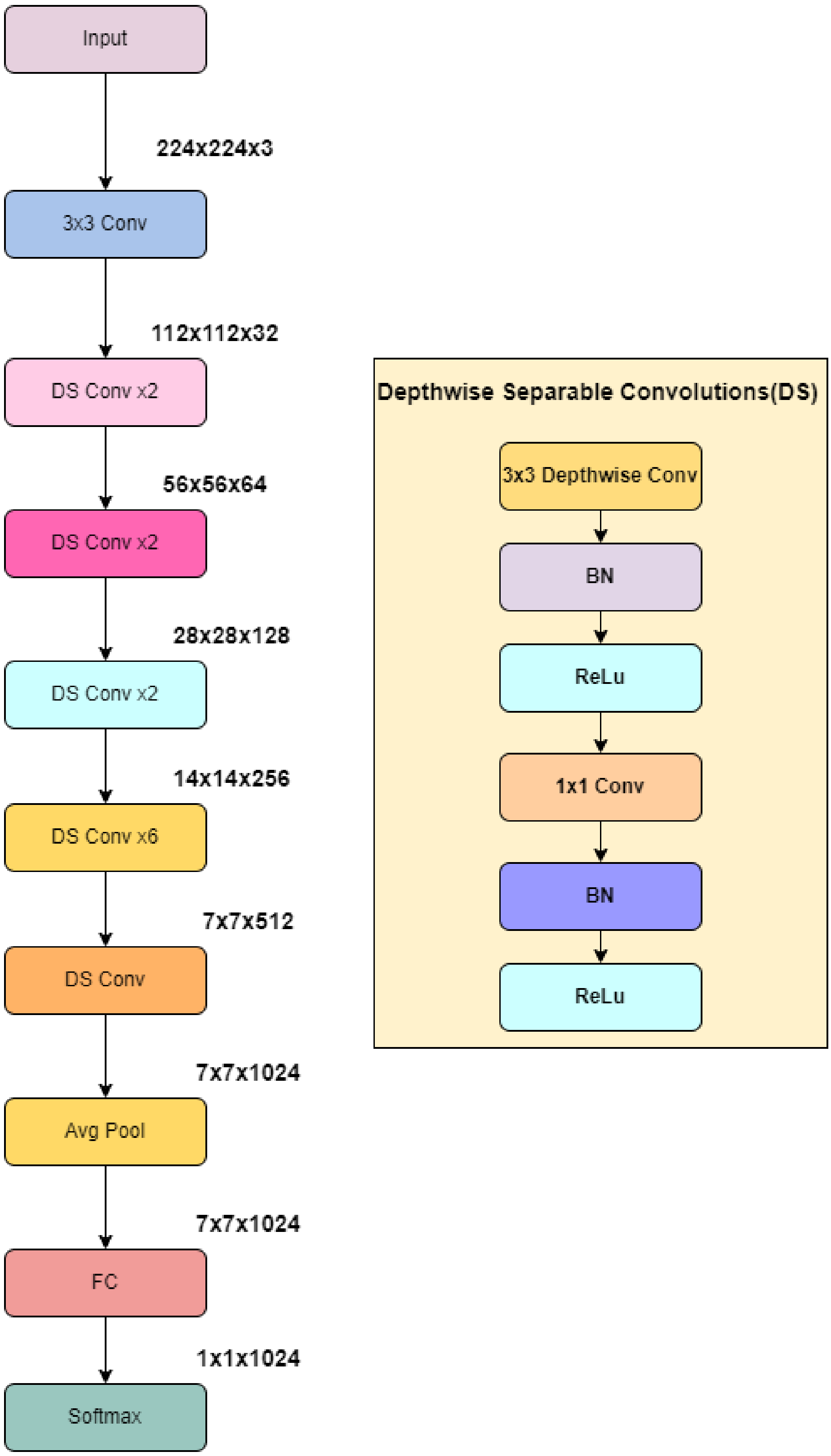

Figure 4.5: Architecture of MobileNet
[20]

E. ResNet-50: The ResNet architecture can be divided into a number of different layers, one of which is the ResNet-50. Due to the fact that it strikes a healthy balance between the complexity of the model and its performance, it finds widespread use Among several uses of computer vision, most notably picture classification. ResNet-50 is frequently pre-trained using extensive image datasets like ImageNet, which includes millions of labelled photos drawn from a wide variety of categories. [34] During the preliminary training phase, the model is instructed to recognise several overarching visual patterns and characteristics. This first training enables the model to acquire a broad spectrum of visual information, which is then able to be honed in on certain tasks for further improvement. Along the same lines as the utility of other pre-trained models, ResNet-50's potential for transfer learning is one of its primary advantages. On a variety of image classification benchmarks, ResNet-50 has exhibited outstanding performance.With 1.2 million training pictures and 1,000 categories for classification, it has achieved top-tier accuracy in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Because of its deeper design, ResNet-50 is able to capture more complicated patterns and features, which ultimately leads to improved performance in representation learning and classification.

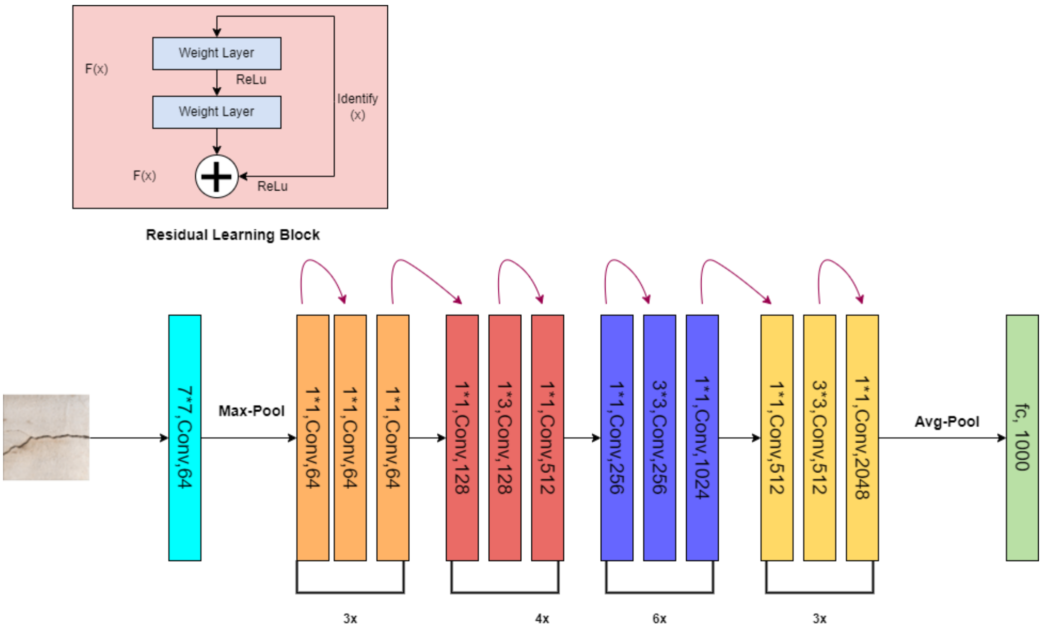

Figure 4.6: Architecture of Resnet-50
[24]

Chapter 5

Result and Analysis

This study considered evaluation metrics like Precision, Recall, and F1-score. The accuracy, precision, recall, and f1-score of the Test results are displayed in the classification Report, a statistic used to evaluate performance.

Accuracy: The fraction of accurate predictions is indicated by the classification problem's accuracy. By splitting out all of the anticipated data by the entire estimated data that was accurate, it is calculated. A model's performance is measured by accuracy, which contrasts the proportion of accurate forecasts to all other predictions. It is typically used as a concluding statistic to determine whether a categorization model is generally effective.

Precision: Precision is the proportion of correctly predicted predictions (i.e.,how many accurate positive forecasts there were) among all positive predictions which is made by the model (true positives plus false positives). It is a measure of how well the model can identify instances of positivity and lower the number of false positives. With low false positives and high accuracy, a model is less likely to incorrectly categorize a counter-example as positive.

Recall: The percentage of correctly predicted outcomes (i.e., the number of correctly predicted positive outcomes) out of all truly excellent examples in the data is known as recall, which is also known as sensitivity (true positives plus false negatives). It assesses how well the model can distinguish each positive case with accuracy and minimize the number of false negatives. As there are fewer false negatives, high recall makes it more likely that the model will properly identify all positive cases.

F1-Score: The F1-score, which of these two figures is the average, provides a complete picture of Precision and Recall. It performs at its highest level if Precision and Recall are equal. When class distributions are imbalanced—that is, when one class contains significantly more examples than the other—accuracy can be a valuable indicator for assessing a model's performance, but it can also be deceptive. In these situations, a model that regularly predicts the majority class could be quite accurate, but it would not be a model that was preferred. This condition is better explained by other metrics including accuracy, recall, and F1-score.

$$\text{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{5.1}$$

$$\text{Precision} = \frac{T_p}{T_p + F_p} \tag{5.2}$$

$$\text{Recall} = \frac{T_p}{T_p + F_n} \tag{5.3}$$

$$F_1 \text{ score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5.4}$$

Here,

T_p (True Positive) = Monkeypox patient identified

T_n (True Negative) = Monkeypox patient identified correctly.

F_p (False Positive) = Non-Monkeypox patient identified incorrectly.

MobileNet Model Accuracy: For MobileNet we began the data pretreatment phase by normalising pixel values. In order to achieve the best outcome we used adam optimizer to get the following values: we receive an accuracy of over 97.6%, a precision of 96.9%, recall of 96.8% and a F_1 score of 96.8%.

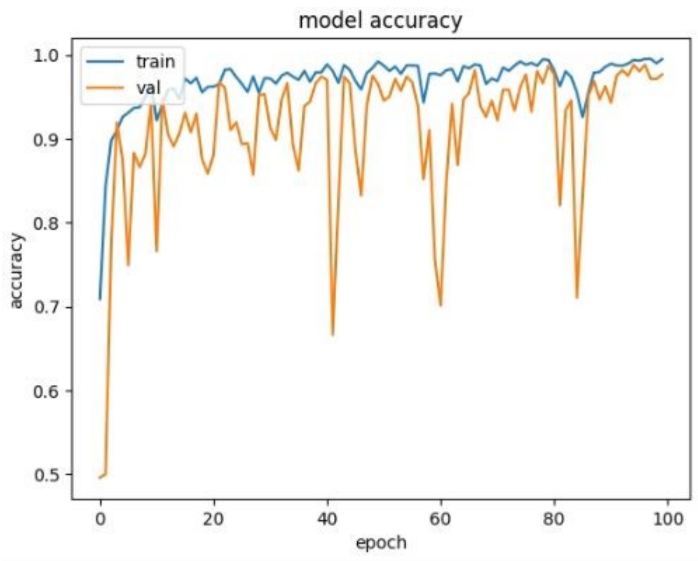

Figure 5.1: Model accuracy of MobileNet for each epoch

InceptionV3 Model Accuracy: The Inception V3 model optimized the network using a variety of techniques for better model adaptation. Here, we receive an accuracy of over 94%, a precision of 94.9%, and a recall of 94%.

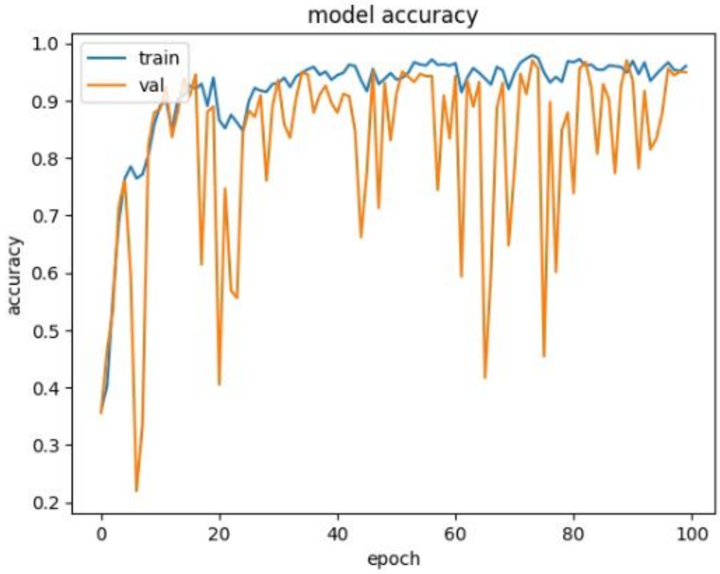

Figure 5.2: Model accuracy of InceptionV3 for each epochs

Xception Model Accuracy: According to early computational findings, our suggested strategy in combination with Extreme Inception (Xception) was capable of differentiating between people who had and did not have monkeypox with an accuracy of 98.6% in Studies. In this xception model, the precession is 98.9%, recall is 98.9% and f1-score is 98.9%. A complex depth-wise separable convolution neural network design is called Xception. Google scientists were behind its creation. Google saw convolution neural network inception modules as only a transitional stage between the regular convolution and the depth-wise separable convolution process.

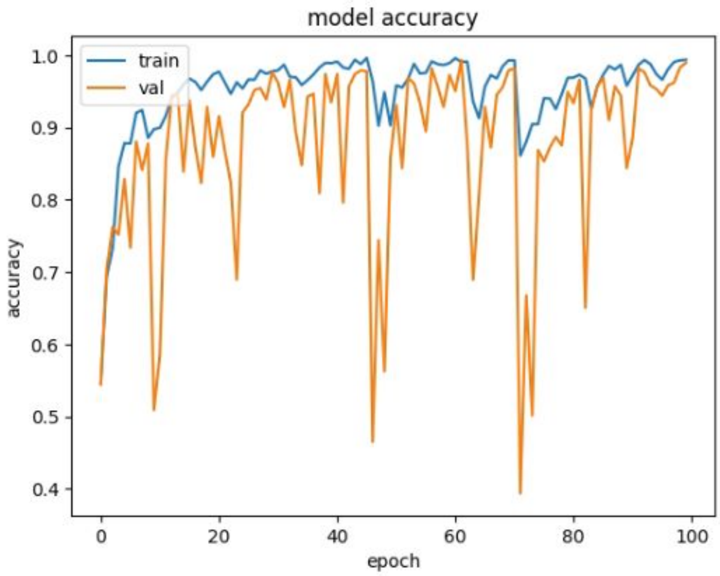

Figure 5.3: Model accuracy of Xception for each epoch

Resnet50 Model Accuracy: We began by performing some initial processing on the data in order to normalize the pixel values and improve the data-set so that it could be utilized more successfully for generalization. We trained the model using the help of gradient descent optimization's approaches (Adam optimizer) so that it can produce the finest possible outcomes.

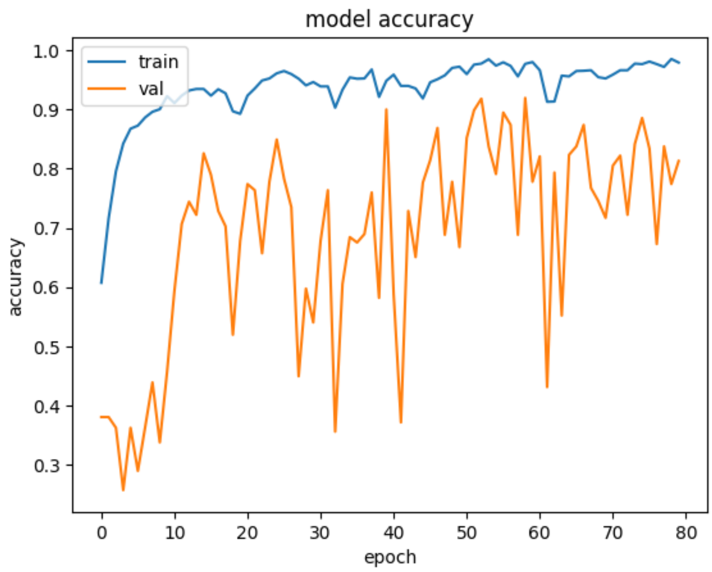

Figure 5.4: Model accuracy of Resnet50 for each epoch

DenseNet121 Model Accuracy: In addition, we trained the densent121 model with the help of Adam optimizer. We achieve an accuracy of over 82% here, while the precision is 84.3%, and the recall is also 82%.

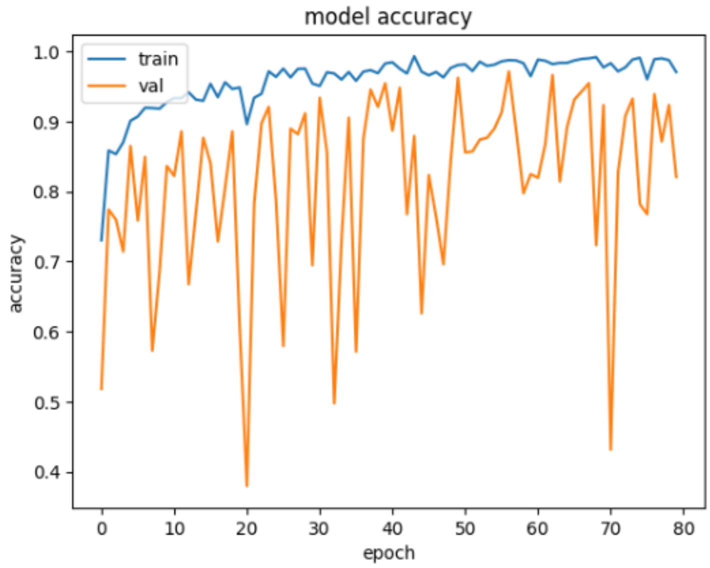

Figure 5.5: Model accuracy of DenseNet121 for each epoch

5.1 Model Loss

To determine how successfully a neural network reproduces test data, researchers use a loss function to compare expected and actual output values. During training, we aim to reduce this gap between actual and predicted results. A neural network's loss function calculates how far the model's prediction differs from the true result. The loss function can be used to derive the gradients for weight updates. The cost is equivalent to the average sum of losses. In order to make sense of the data at hand, machine learning models like neural networks try to determine the underlying probability distribution. Maximum likelihood estimation provides a common statistical foundation for model construction in machine learning.

Losses incurred by the model during the training and testing phases. Taking a look at the figure might help with the determination. This means that in order to develop a model that accurately represents the distribution of our data, we need to search for a set of parameters and a prior probability distribution, such as the normal distribution. If we are successful in our search, we will then be able to create a model that accurately represents the distribution of our data.

Except Densenet121 we saw that in MobileNet, InceptionV3, Resnet50 and Xception the model loss is decreasing. This is so that the model can learn in Machine Learning, which uses the loss function. The goal of the model is to lessen the magnitude of the loss. This is achieved by using techniques like gradient descent, which adjusts the model's parameters based on the outcome of the loss.

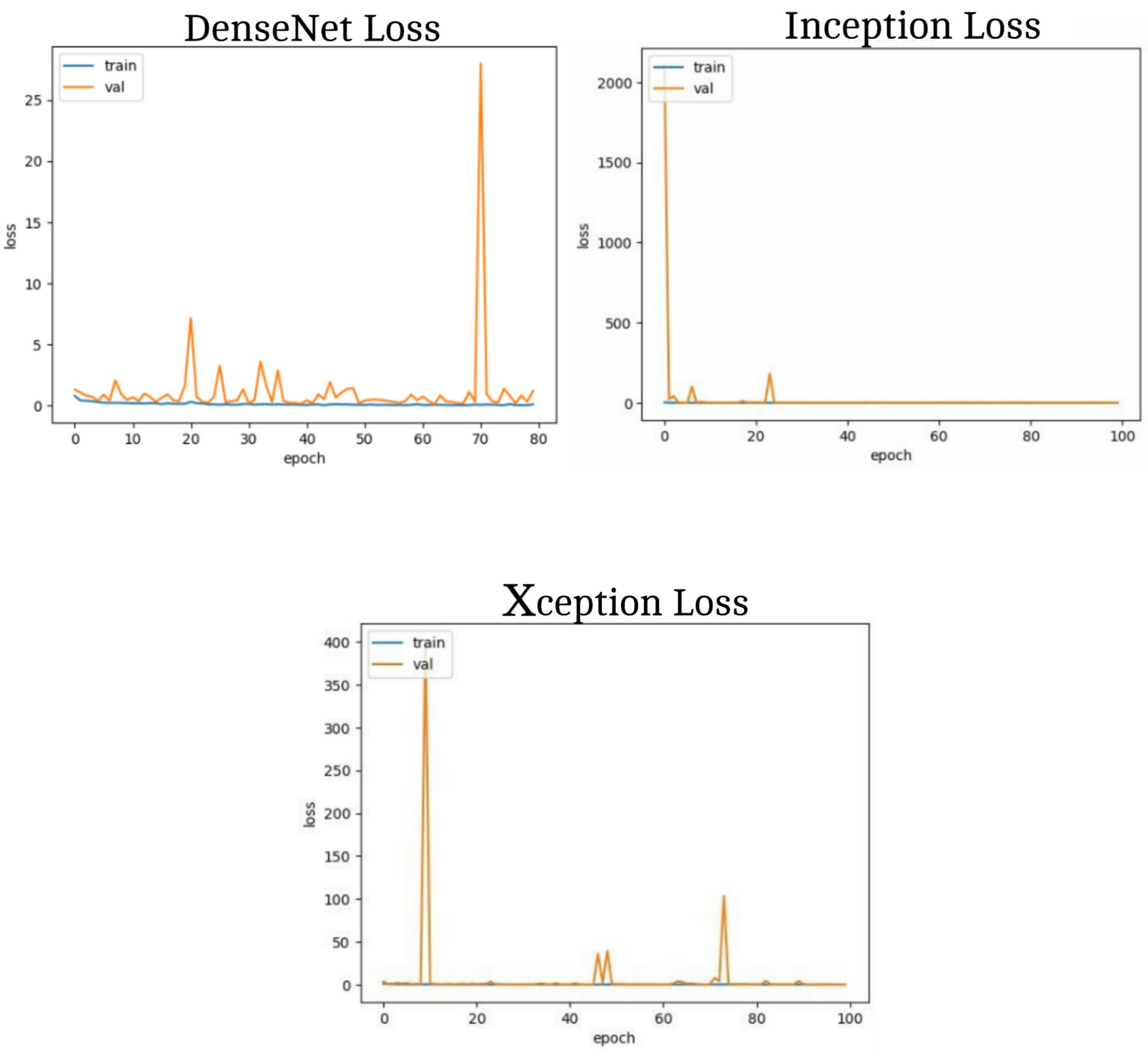

Figure 5.6: Model Loss of Mobilenet Epoches

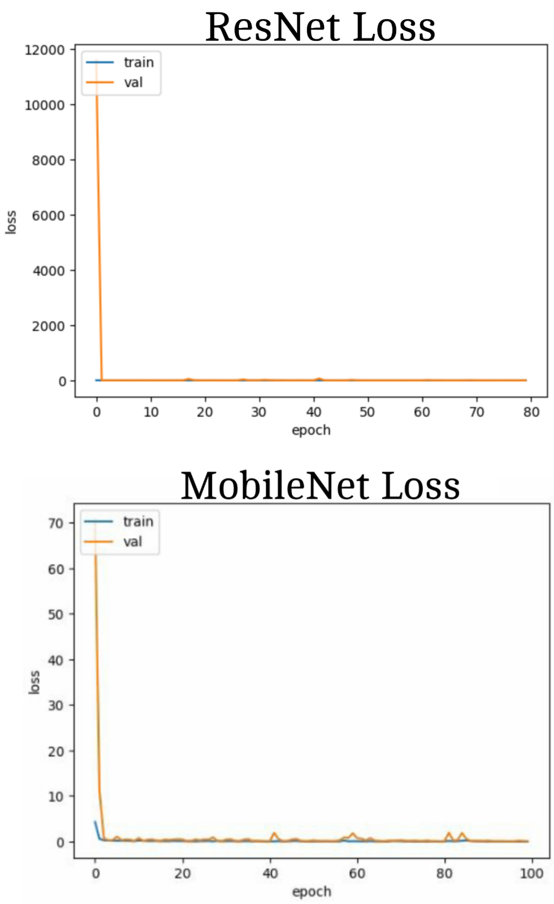

Figure 5.7: Model Loss of Mobilenet Epochs

Table 5.1: Preliminary Computational results of the ML algorithms used during this studies

Model	Precision	Recall	F_1 Score	Accuracy
Mobilenet	0.969	0.968	0.968	0.976
Inception V3	0.949	0.948	0.948	0.949
Resnet50	0.848	0.812	0.829	0.812
Densenet121	0.843	0.820	0.831	0.820
Xception Model	0.989	0.989	0.989	0.986

5.2 Confusion Matrix

For the purpose of providing the prediction summary, a confusion matrix is utilised. For each class, it shows how many forecasts were right and wrong. It helps to delineate the classes that other classes confuse with the classes of the model. The effectiveness of image categorization is frequently evaluated quantitatively using a confusion matrix (also known as an error matrix). It is a table that shows the relationships between a reference image and the categorization result. Prediction-making was a component of the analysis.

Using the models discussed previously. The confusion matrix is divided into two classes: positive and negative. Because the positive class reflects the abnormal class or conduct, it is frequently underrepresented in comparison to the opposite class. In contrast, the negative class reflects normalcy or typical behavior.

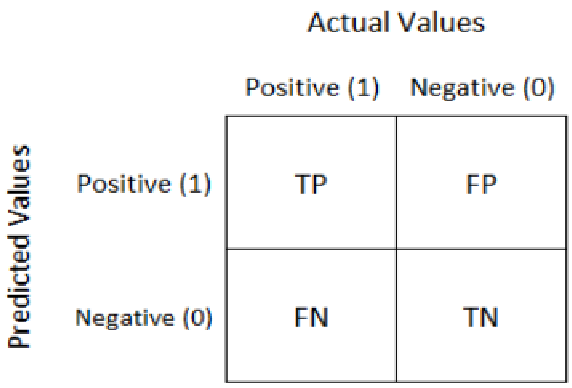

Figure 5.8: Confusion matrix

It shows that the algorithm's efforts to reduce false negatives and positives were consistent. True negatives are pictures that were successfully recognized as merely not having monkeypox, as opposed to true positives, which are pictures that were correctly identified as having monkeypox. Here, the acronyms "FP" and "FN" stand for the number of real negative instances that were categorized as positive and real positive cases that were classified as negative, respectively. False positive photos are those that were wrongly determined to have monkeypox, whereas false negative images were determined to not have monkeypox in error.

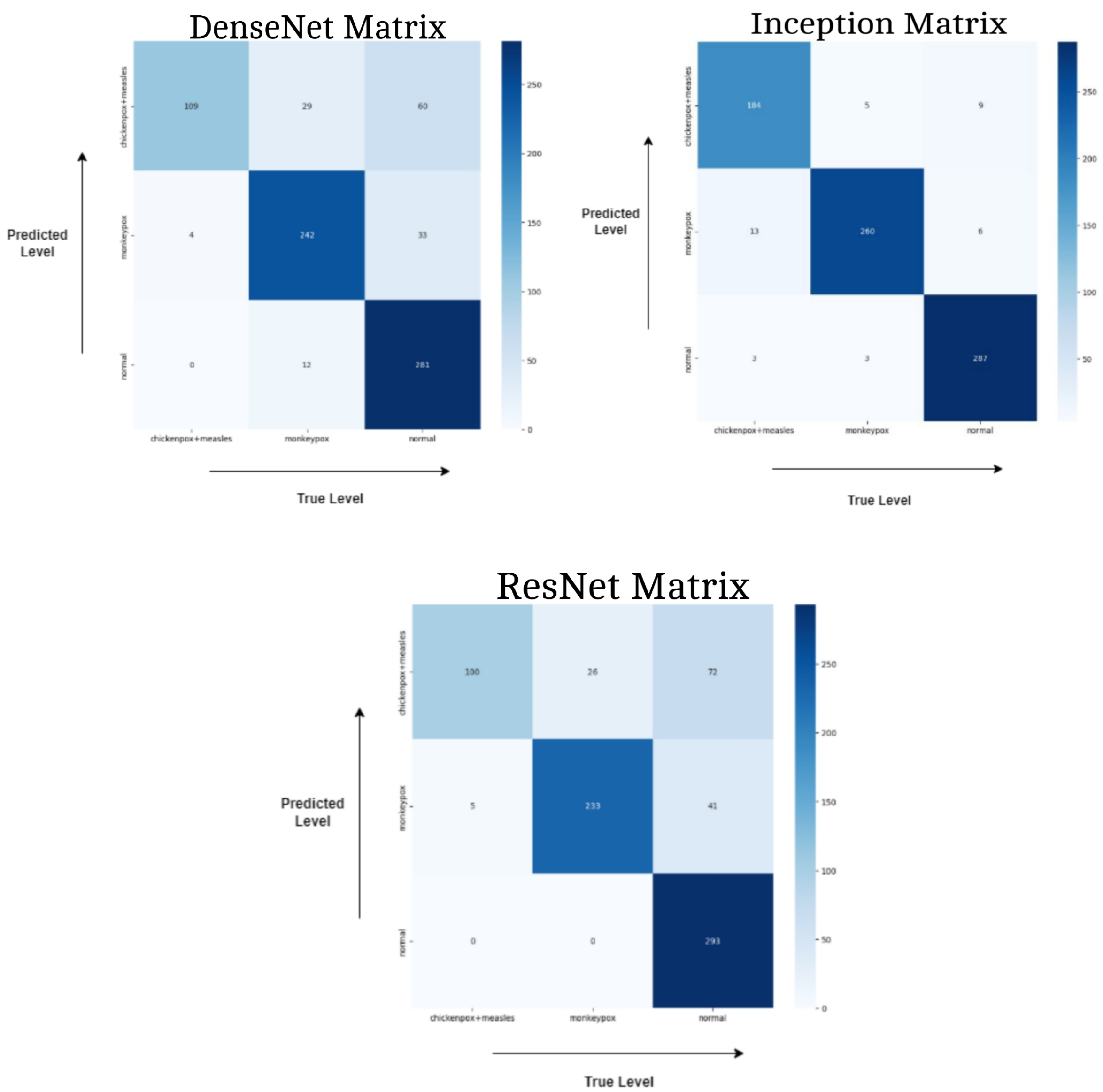

Figure 5.9: Confusion matrix for each model

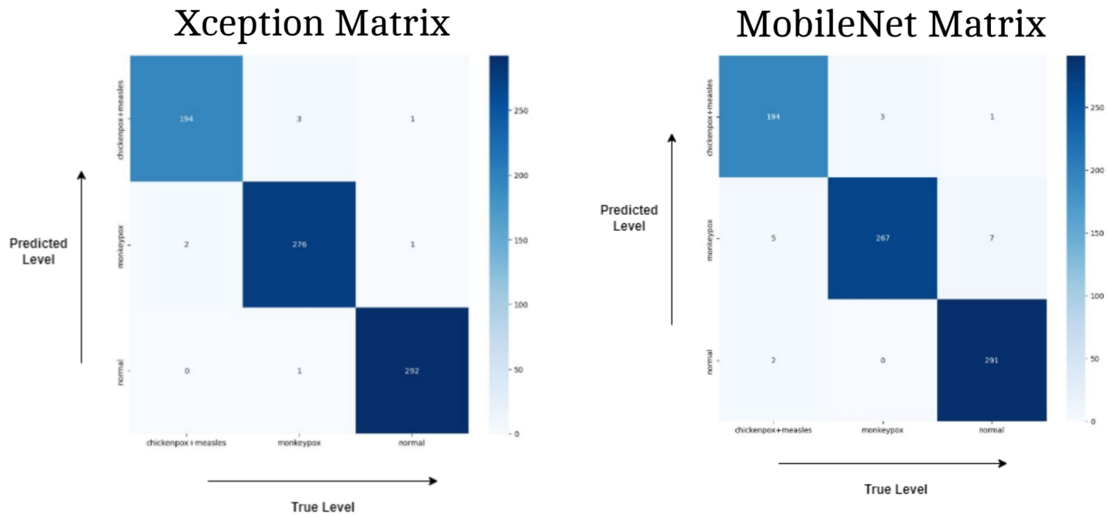

Figure 5.10: Confusion matrix for each model

The analysis tried to make predictions using the models covered above. The findings for the most successful model, xception, are shown as confusion matrices in the graphic below. It's also important to note that the model has never identified a healthy person as having monkey-pox. This is shown by the confusion matrices' healthy skin row, where no healthy skin was discovered to have monkey-pox.

5.3 ROC (Receiver Operating Characteristic)

The Receiver Operating Characteristic (ROC) curve is a visual depiction that illustrates the effectiveness of a binary classification model at different classification thresholds. This curve is also known as the Receiver Operating Characteristic. It is an essential instrument for evaluating and contrasting the quality of prediction models, in particular in situations when there is an imbalance in the distribution of classes.

The receiver operating characteristic curve is constructed by plotting the true positive rate (TPR), also known as sensitivity, on the vertical axis, and the false positive rate (FPR), which is the complement of specificity, on the horizontal axis. This creates a relationship between the two variables. Changing the model's classification threshold, which determines how confident the model has to be before classifying an instance as positive, is how the curve is created. This threshold specifies how confident the model needs to be. When the threshold is changed, the TPR and FPR values are also altered, which causes the points on the ROC curve to move to new locations.

The ROC curve offers a straightforward method of visualising and comprehending how the sensitivity and specificity of a model are affected by changes in the threshold value. The ROC curve is a useful tool that may be utilised to assist in the selection of an acceptable classification threshold that is in accordance with the desired balance between true positives and false positives. The area under the receiver operating characteristic curve, also known as the AUC-ROC, is a single statistic that quantifies the overall performance of the model across all of the available thresholds. It can be anywhere from 0 to 1, with 0.5 indicating a random classifier and 1 indicating a flawless classifier. Its range is 0 to 1. In general, more discrimination and prediction capacity can be inferred from an AUC-ROC value that is higher. When dealing with imbalanced datasets, in which one class is substantially more abundant than the other, the ROC curve and the AUC-ROC are very helpful diagnostic tools. When compared to accuracy, which can be deceiving in situations like this, they provide a more holistic view of model performance.

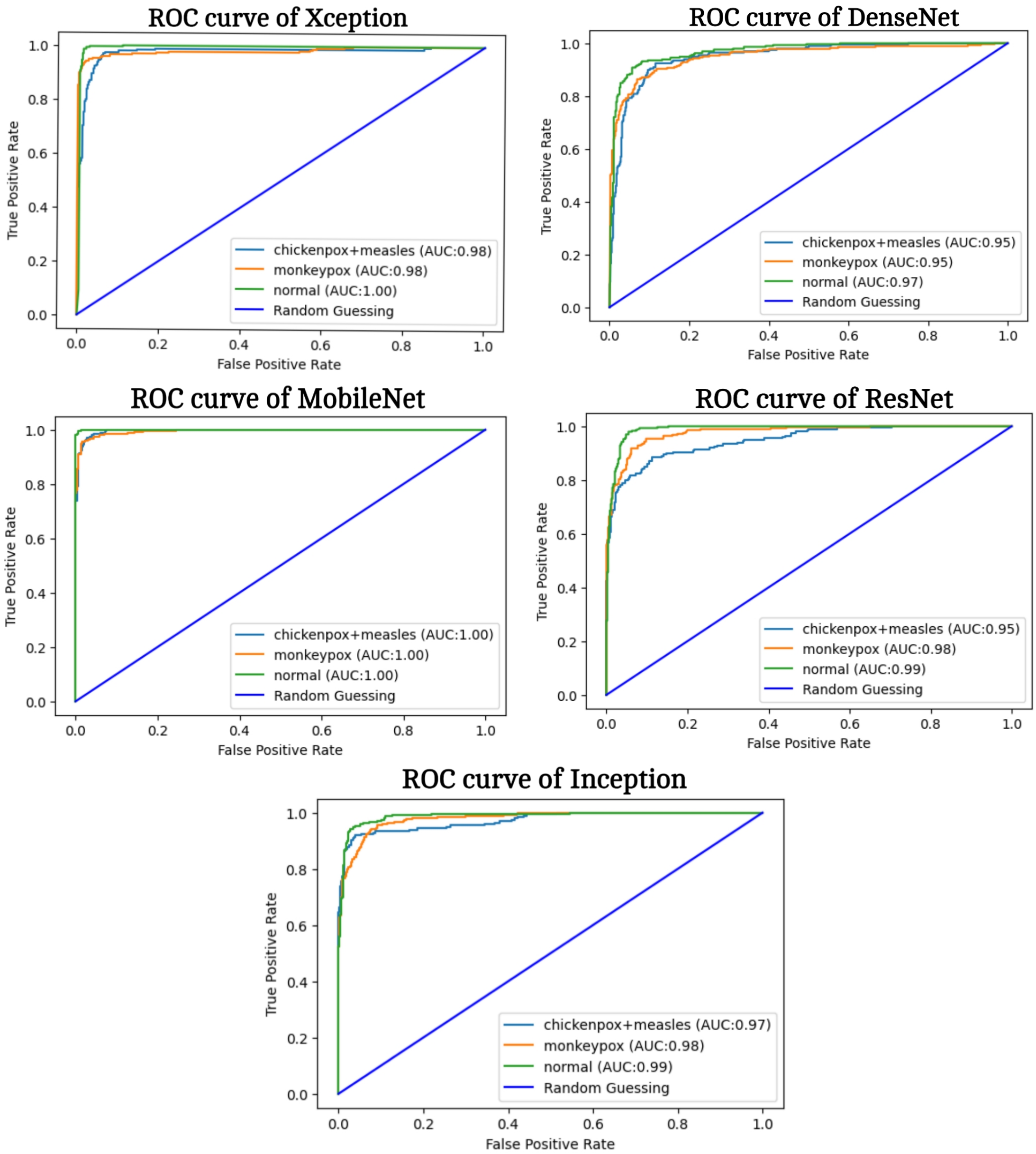

Figure 5.11: ROC curve of each Model

The Receiver Operating Characteristics (ROC) curve analysis we conducted here involved several popular convolutions neural network (CNN) architectures, namely Xception, InceptionV3, MobileNet, DenseNet121 and ResNet50. The area Under the ROC curve (AUC) values we obtained for each of these models are as follows:

MobileNet stand out with an AUC of 1.00, which suggests that it achieved near perfect classification performance on our dataset. This could be due to its efficiency and suitability for various applications, especially those with limited computational resources. Xception also performed exceptionally well with AUC of 0.98, indicating high discriminative power in distinguishing between the classes. InceptionV3's AUC of 0.97 demonstrates its competence in our classification task. This model's inception modules effectively capture complex features within the data. Both DenseNet121 and ResNet achieved an AUC of 0.95.

Table 5.2: AUC of the classes from ROC curve

Model/Class	Chickenpox+Measles	Monkeypox	Normal Skin
Xception	0.98	0.98	1
Inception V3	0.97	0.98	0.99
MobileNet	1	1	1
DenseNet	0.95	0.98	0.99
ResNet	0.95	0.95	0.97

5.4 Discussion

The study found that the chosen algorithms are reasonably good at detecting Monkeypox in digitized skin scans. Therefore, Xception, on the other hand, has the best metrics. That confirms the findings of the study here. From our study, we can find that Xception obtained an F1-score of 0.989, better than the present report's results.This research complements their findings by evaluating the model against others like it to guarantee satisfactory outcomes.

From our study, we get better accuracy, precession call, and f-1 score in MobileNet and Xception Model. Because the data was insufficient to use train, validation, and splitting operations.

In Xception, we found a mean accuracy of 98.6%, and a precession of 0.989. F-1 score of 0.989 and mean recall of 0.989. In the mobilenet model, the mean precession is 0.969, the mean recall is 0.968, the mean f-1 score is 0.968 and the accuracy is 97.6% . The scores are close to Xception but in Xception, we get more accuracy and better precession calls.

More specifically, when compared to the measles and monkeypox viruses, our technique can distinguish between chickenpox and normal photos.As a consequence of this, it is extremely important to differentiate it from other conditions that display themselves as sores on the skin. This study only looked at four different labels, however previous research has looked at a far larger number. Several skin ailments are being investigated. Apart from Monkeypox, the 'many models' technique has also been used to detect other diseases. One of the benefits of using a variety of models is that the researcher is given the opportunity to evaluate each one and determine which one has produced the best results. Images of monkeypox may be hard to come across right now due to their scarcity. A number of the photographs on Google may not be of the disease, although they are labeled as Monkeypox by certain websites. Before incorporating skin scans in model prediction and training, researchers must pay a microbiologist to evaluate them. From the literature review part, we get that most of the skin disease studies classification systems use custom CNN, Inception-ResNet-v2, VGG-16, and so on. In our study, we get more accuracy and an f-1 score than any other models.

Table 5.3: Summary Table

Model	Precision	Recall	F_1 Score	AUC	Accuracy
MobileNet	0.969	0.968	0.968	1.00	0.976
InceptionV3	0.949	0.948	0.948	0.97	0.949
ResNet50	0.848	0.812	0.829	0.95	0.812
DenseNet121	0.843	0.820	0.831	0.95	0.820
Xception	0.989	0.989	0.989	0.98	0.986

5.5 Model Deployment

We developed a web app to demonstrate the accuracy of our best model. This web app can accurately detect the images of all three classes. To create this web app we used the following tech stack:

Table 5.4: Tech Stack for Model Deployment

Component	**Description**
Operating System	Windows 11
Data Visualisation	Matplotlib and Seaborn
Data Analysis	Pandas
GPU	T4 GPU from Google Colab
Machine Learning Framework	TensorFlow
Python Version	3
Programming Language	Python
Web Application	Streamlit

The app goes through the following procedure to classify and display the results from an input image.

1. Load the saved Keras model: We go through the model folder stored in the server and load all the files with a .h5 extension.

2. Load the label files: The label file contains the indexes of all the classes. 0 is for "Normal" , 1 for "MonkeyPox" and 2 for : ChickenPox+Measles".

3. Take image input from users: We use Streamlit to show a button to the user that takes an image input.

4. Resize it to (244,244): Our model is trained on images with 244,244 resolution. However, the image the user uploads may not use the same resolution. Hence, we do some image operations to match it closer to the images that the model was trained on.

5. Normalize the image: We normalize the image array to a value of 0 to 1.

6. Predict the image class: After that, we use the model to predict the image. The prediction returns the index of the class it belongs to. We use the label file loaded before to get the class.

7. Read the confidence score: The prediction also returns a confidence score. The score is multiplied by 100 for better readability.

8. Display the class and a confidence score to the user: Finally, we format the class name and confidence score with Markdown and display the result of the user.

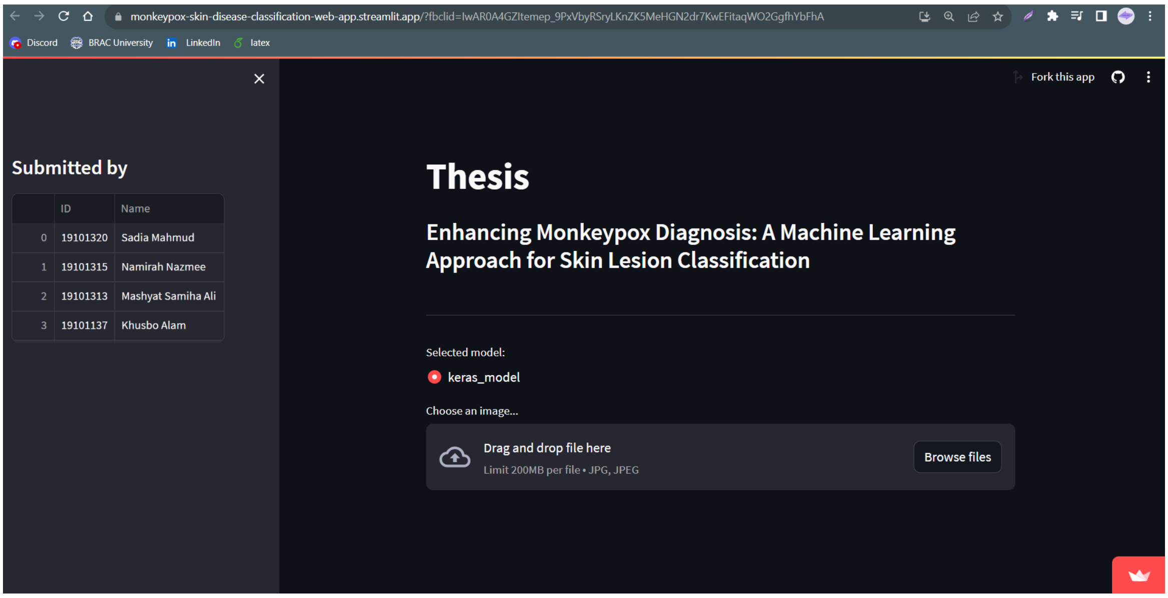

Figure 5.12: Hompage of the website

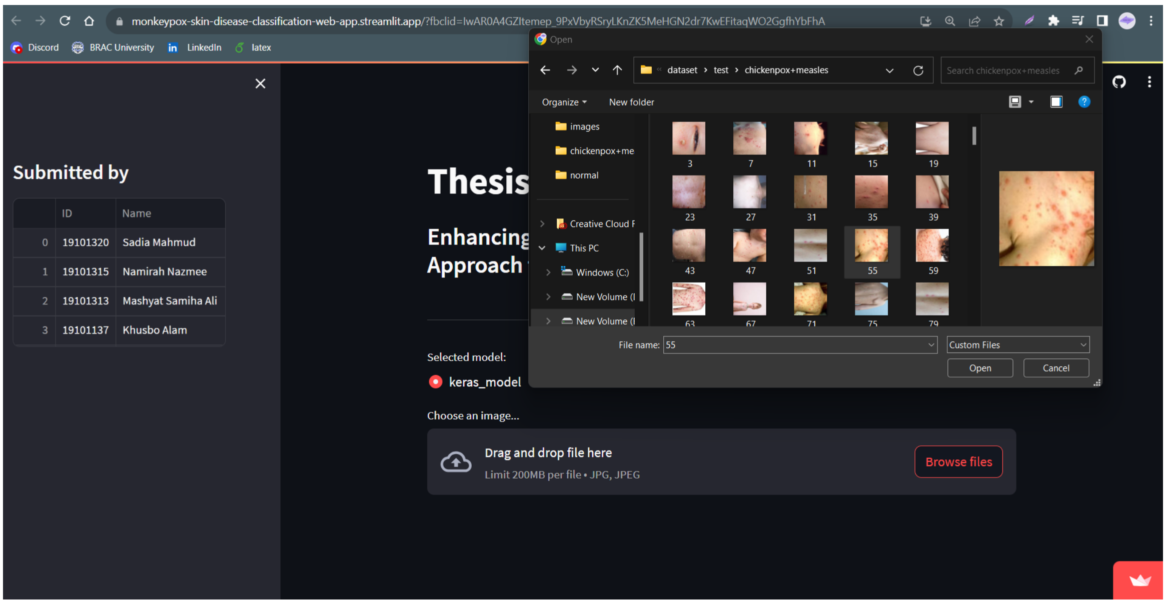

Figure 5.13: Image selection

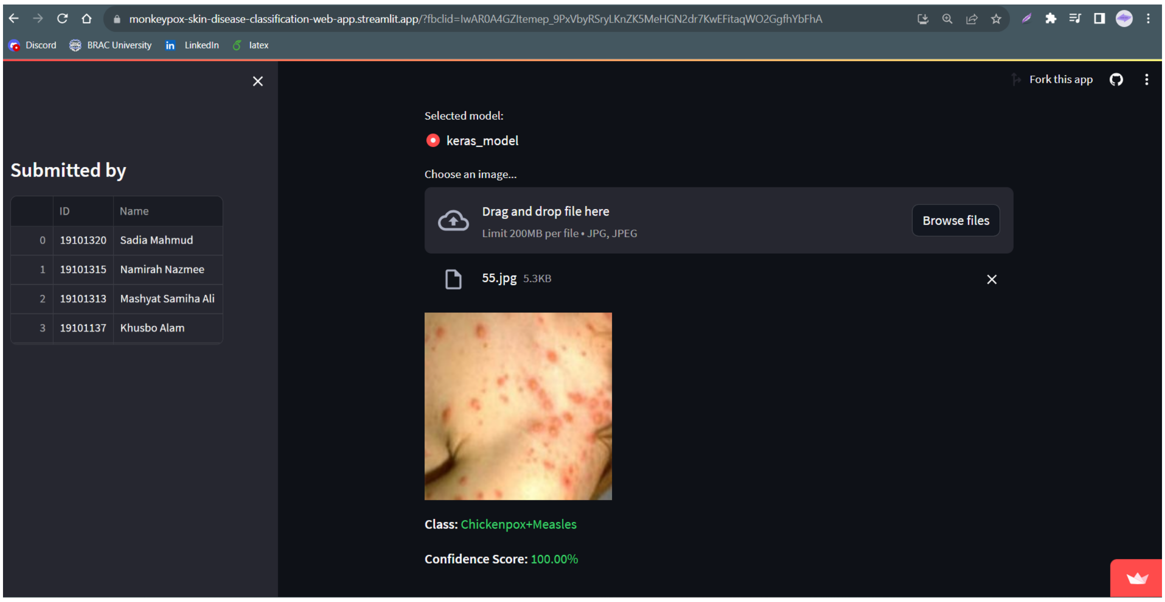

Figure 5.14: Result presentation

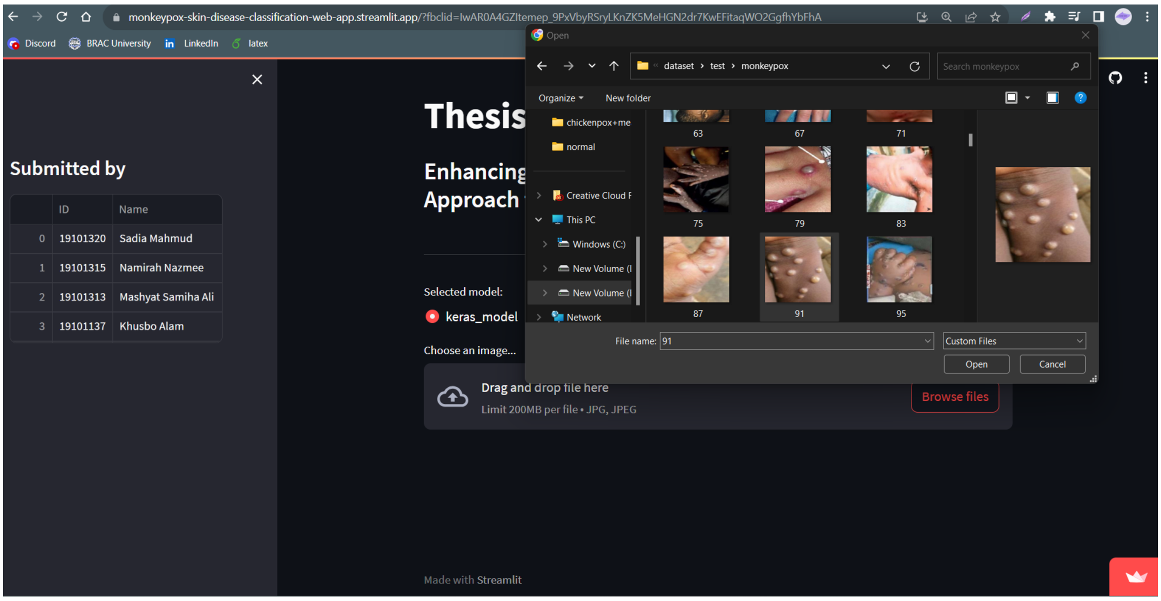

Figure 5.15: Image selection

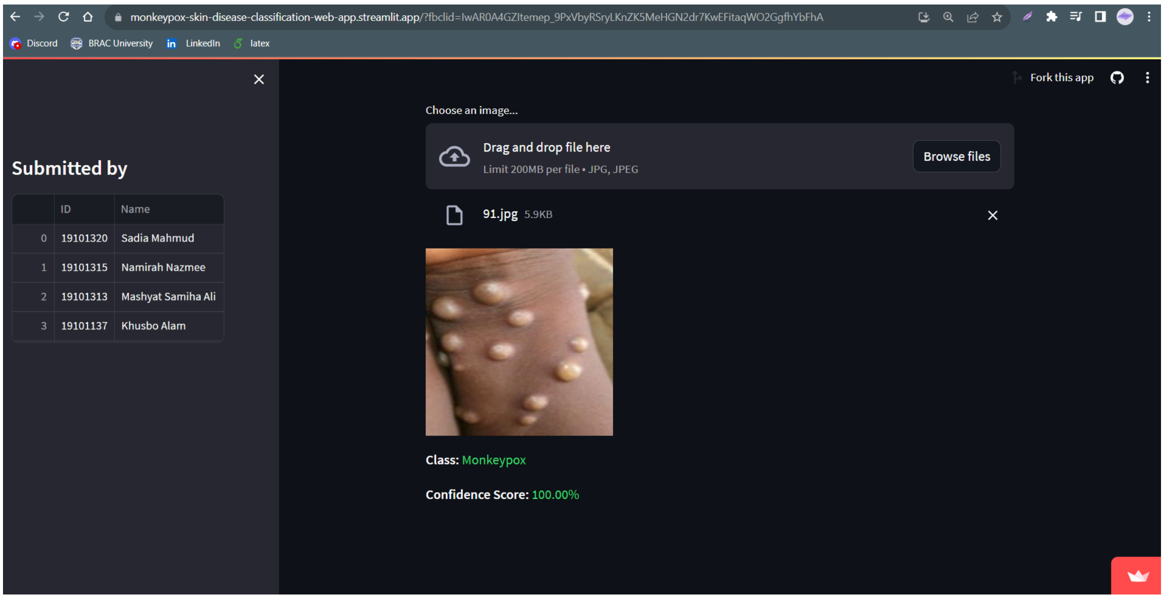

Figure 5.16: Result presentation

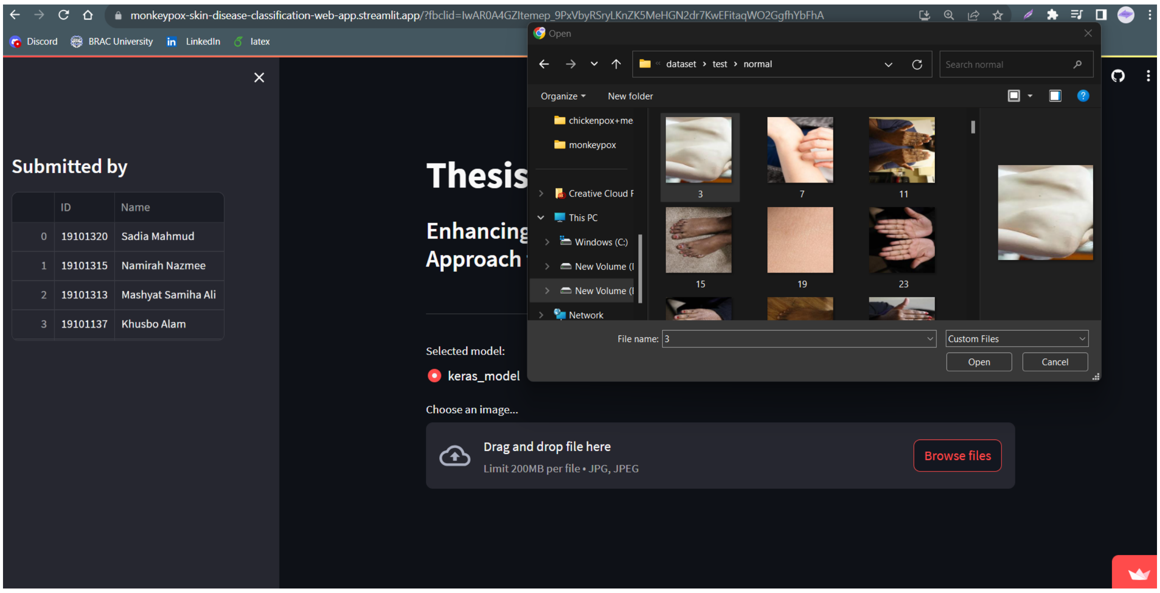

Figure 5.17: Image selection

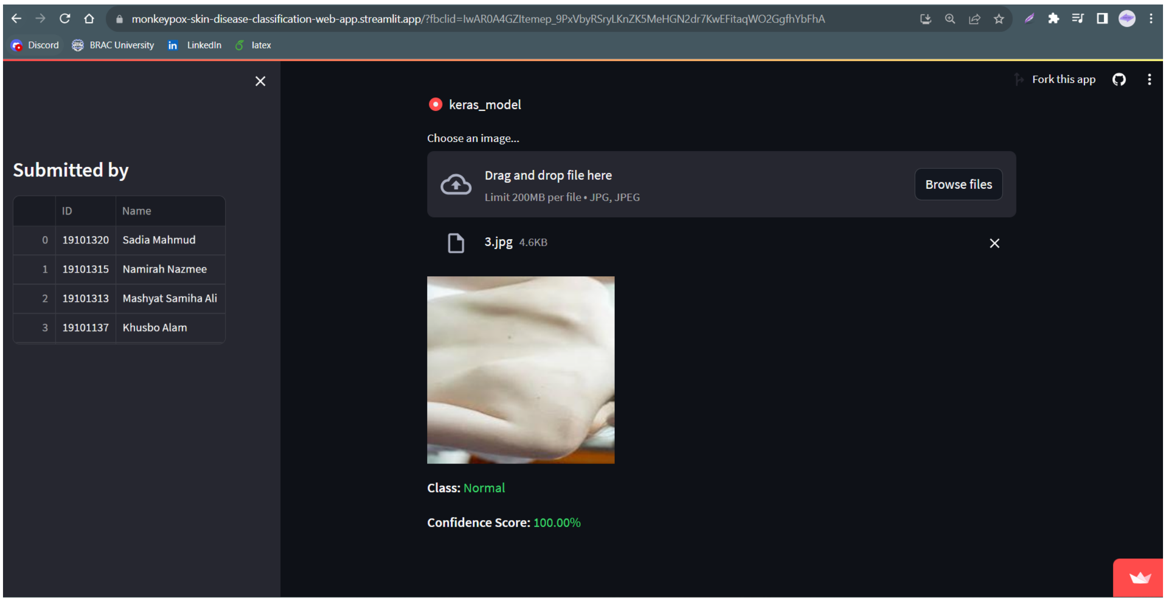

Figure 5.18: Result presentation

Chapter 6

Conclusion and Future Work

6.1 Conclusion

In the most recent research, machine learning techniques are being put to the test in order to determine whether or not digital skin photographs can accurately diagnose monkeypox. The findings suggested that the models that were consulted operated in a manner that was virtually identical. However, Xception stood out from the rest due to its superior accuracy and F1- ratings. Due to the fact that no healthy skin was found to have a future, the diagnosis of healthy skin was extremely accurate in regards to the onset of chicken pox and monkey pox.

For efficient and prompt treatment of chickenpox and monkeypox, early diagnosis is essential. As a result, epidemics and disease-related fatalities are avoided. The similarities between the symptoms of chickenpox and monkeypox might cause misdiagnosis, especially in endemic regions with a dearth of communicable disease specialists.

The findings of this study demonstrate that a DL framework is capable of accurately classifying widely known skin lesions linked to chickenpox and monkeypox. A DL strategy can be used independently or in conjunction with communicable disease experts in endemic areas to address the current monkeypox outbreak. This would help with the condition's early diagnosis. Future outbreaks of chickenpox and monkeypox will be prevented as a result.

6.2 Future Work

We developed a web application that allows users to upload photos and the application will determine whether they have monkeypox or not. We want to upgrade the app in the future in order to improve the user experience. In future, we will prioritize expanding our data to enhance the websites performance. We'll make sure the software can handle the computational and memory restrictions without compromising the user experience. To ensure that the web app continues to function even if the edge device's internet connection is broken, we will activate offline capabilities for it. Additionally, we will tighten security measures to protect user data and privacy while installing the web app on edge devices. Last but not least, by putting in place procedures, we can make sure that the web app and all of its components are automatically updated with the newest features, bug fixes, and security updates on edge devices.

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