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Diabetic Foot Ulcer Prediction and Recommendation Tool

In partial fulfilment of the requirements for the degree of
Bachelor of Science in Computer Science

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C e r t i f i c a t e

We accept the work contained in the report titled

"Diabetic Foot Ulcer Prediction and Recommendation Tool"

written by

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as confirmation to the required standard for the partial fulfilment of the degree of

Bachelor of Science in Computer Science.

Approved by:
Supervisor: Abdullah

________________________________ (Signature)

December 2024

DECLARATION

We hereby declare that this project report is based on our original work except for citations and quotations which have been duly acknowledged. We also declare that it has not been previously and concurrently submitted for any other degree or award at Bahria University or other institutions.

Enrolment	Name	Signature
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Date : December 2024

Especially dedicated to

My beloved father, mother and grandparents

(Mubasher Manzoor)

My beloved grandmother, mother and father

(Haris Ali Safder)

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We would like to thank everyone who contributed to the successful completion of this project. We would like to express our gratitude to our supervisor, Abdullah, for his invaluable advice, guidance and his enormous patience throughout the development of the research.

In addition, we would also like to express our gratitude to our loving parents and friends who have helped and given us encouragement.

Mubasher Manzoor

Haris Ali Safder

Abstract

This research aims at filling the existing gap of Diabetic Foot Ulcers (DFUs) through deploying a mobile application involving machine learning to enhance early detection and intervention. The application trained the arising model to predict DFUs with high accuracy simply by merging not only the features elicited from medical image analysis, but also other features from patient's demographics. Flipping through several machine learning models, the most optimal one is used for classification of DFU. The system incorporates a registration screen for creating the account, a login screen for accesses, and detailed diagnosis screen for uploading medical images with classification and prediction on possibility of DFUs. To communicate with the mobile application and the built machine learning model, Flask web-interface is employed for the development of Application Programming Interface (API) that provides real time predictions and suggestions. This integration benefits healthcare professionals and diabetics by giving warnings about DFU development and seeking treatment immediately. To close the gap between theoretical models and actual applications in the management of diabetic foot, the project will be of importance in promoting knowledge regarding available technological applications for optimal diabetic foot complications management and ultimately, the improvement of patient outcomes in diabetic foot.

Table of Content

List of Tables

List of Figures

List of Abbreviations

DFU’s	Diabetic Foot Ulcer
API	Application Programming Interface
CNN	Convolutional Neural Network
ML	Machine Learning
GAN	Generative Adversarial Network
SNN	Siamese Neural Network
PSO	Particle |Swarm Optimization
CV	Computer Vision
DM	Diabetic Melitious
YOLO	You Only Look One
Smote ENN	Synthetic Minority Over Sampling Technique - Edited Nearest Neighbor
IDE	Integrated Development Environment
PC’s	Personal Computer

Chapter 1

Introduction

1.1. Background

Diabetic foot ulcers (DFU) are one of the prevailing and serious issues connected with diabetes, influencing the quality of life and raising costs for the health care systems tremendously. Special attention should be paid to recognize and treat Diabetic Foot Ulcers at the initial stage to avoid progression to infection or amputation. Other techniques of diagnosis involve physical checks by medical personnel which may be tiresome and inaccurate because of human involvement. Hence, the demand for intelligent diagnostic tools in detecting the DFUs at the early stages has increased rapidly by incorporating image processing and machine learning methods.

It has been established that the use of image analysis in the diagnosis of diseases significantly works, especially in dermatology. Using the idea of machine learning for DFUs, it has been found that models especially based on Convolutional Neural Network (CNN) have shown some ability to identify the images of the wounds and to determine whether there is something wrong with them or not. By having these models trained on such a large dataset used in foot ulcer image classification, efficient diagnostic accuracy and speed can be affected with the models also able to pick out signs that a human clinician might easily miss.

This is Deployment of the Diabetic Foot Ulcer Prediction and Recommendation Tool: The main aim of this project is to use a– Image processing, b– Machine learning models for identifying and categorizing the DFU from the medical images. The dataset includes over 9,500 images from four categories: They were labelled as Infection, Ischaemia, Normal and Abnormal. The preparation step of the model uses some preprocessing, data augmentation, and balancing of data. Furthermore, different machine learning models namely SimCLR, Logistic Regression, Random Forest, and EfficientNetB0 were trained and tested to build the efficient diagnostic tool to enhance the healthcare professionals in diagnosing DFUs with desirable level of precision.

1.2. Problem Statements

The existence of DFUs is another emerging problem for diabetic patients, who can develop infections and must undergo amputations if they are not diagnosed at the start. The existing techniques for diagnosis of DFUs are mostly clinical assessment, which by nurses and physicians, and hence can be non-specific and may take long time. As diabetes cases increase, it is for this reason that there is high demand for an automated, accurate and efficient tool for early detection to enhance patient's life and equally relieve the stress of those in health facilities.

1.3. Aims and objectives

This project, therefore, seeks to come up with a Diabetic Foot Ulcer Prediction and Recommendation Tool, which applies artificial intelligence and machine learning to identify and categorize the DFUs from images received from the clinic. These objectives include: (1) data acquisition and preprocessing of large scale DFU images, (2) data enhancement and balancing of the dataset, (3) training and testing of different ML models including SimCLR, Random Forest and EfficientNet B0, and (4) integration and deployment of the final selected model in a user-friendly mobile application interface for easy accessibility by health care personnel.

1.4. Scope of Project

This work revolves around one of the project goals on design of image based diagnostic tool for DFUs with the assistance of machine learning approaches. It involves feature extraction and selection, data enhancement and augmentation and identification and model training to classify images such as Infection, Ischaemia, Normal and Abnormal categories with improved accuracy. The tool is designed for application in clinical environments and is expected to help clinicians make correct diagnosis in the least possible time. The project also consists of implementing the model into a mobile application so that it can be used in real life clinical practice.

Chapter 2

Literature Review

2.1. Papers

To this effect, this research focuses on the identification of ischemia and infection in diabetic foot ulcers (DFUs) using deep learning models such as ResNet, Inception, and an ensemble CNN. These models yielded accuracies of 87 percent to ischemia and infection while 90 percent to ischemia and a 73 percent infection accuracy under the ensemble approach. The work also points to data and clinical diversities as well as interpretability suggesting the ability of automated solutions to help in diagnosing with efficiency and without issues such as amputation of limbs [1]. This review aims to discuss the potential of Computer Vision (CV) and Machine Learning (ML) in the context of DFU because they can automate classification, monitoring, and prediction. The application of these technologies appears to give real time feedback to the clinician and the patient, cause minimal physical contact, and allows timely follow up. However, knowledge gaps like data quality, external validation, and integration into clinical practice settings are areas that define the work in progress of these technologies [2]. The classifying of chronic wounds is a task for which this work introduces a semi-supervised progressive multi-granularity efficient network model based on EfficientNet and with high F1 scores above 90%. In particular, the method makes use of augmented and unlabeled data to overcome the problem of the small and imbalanced size of the dataset. However, the research is not without those difficulties, including refining Generative Adversarial Network (GAN), using data that has no labels, and boosting the model's ability to generalize [3]. The study improves the current segmentation of DFU through employing HarDNet-MSEG with test-time augmentation and cross-validation that returned with test dice of 0.7063 and 0.7287 on different phases of validation. The method shows good performance in terms of morphological feature extraction which is fundamental for successful DFU handling. Existing challenges are discussed as follows: generalization of the models to other datasets, and the enhancement of model interpretability for clinical applications [4]**.** In DFU segmentation, this work employs SegFormer, a convolutional and transformer-based model, and obtains a Dice coefficient of 69.89% and a Jaccard coefficient of 59.21%. These results reveal impressive characteristics of the deep learning method applied to different scenarios and indicate that accurate and efficient segmentation is within a genuine and viable reach. Some of these limitation areas include enhancing model generalization, strengthening data variation and increasing model's interpretability to enable its clinical implementation [5]. This work integrates YOLOV8m and Faster R-CNN with ResNet101 and applies WBF to improve the localization of DFU, the localization results achieve a mean average precision of 86.4%. Based on these results, our model was superior to conventional benchmarks and showed strong performance in the external validation of DFUC2020 dataset. However, the results of false positives and diagnostic errors suggest there is more work to be done [6]. The proposed DFU-Helper framework uses a Siamese Neural Network (SNN) for the comparative assessment of DFUs at different follow-up visits and demonstrates a macro F1 score of 0.645 for DFU classification. Dialysis data such as the rate of traveling through different stages of the disease can actually monitored effectively through use of this system and its class reference points. However, there are some questions for further research: (a)F1 scores are generally low; (b) dataset diversity; (c)usability improvements [7]. This work adopted Particle Swarm Optimization (PSO) with Alex Net, Google Net, and Efficient Net-B0 for DFU classification with very close to perfect evaluation scores of between 0.82 and 0.97. It proves that the presented models perform better than heavier architectures with similar characteristics but always points out the problem of moving models from research to real-life application and making them work with data collected from the actual environment [8]**.** The research aims at improving the current approaches' accuracy and reducing the time spent on DFU classification using deep ResNet models and transferring learning. Thus, even if the dataset is increased from 146 images to 3000 the best state of art model, ResNet50, has accuracy of 98.67%. The work also supports the use of multiple datasets and data generalization with respect to the real-world environment for broader application [9].

Table 2.1.1: Deep Learning DFU Classification

Article Name:	Diabetic Foot Ulcer Ischemia and Infection Classification Using Deep Learning Models
Problem Statement:	Diabetic foot ulcers or DFUs are a common problem that afflicts diabetic patients, with most of them likely to undergo limb amputation. Of these, two main elements that exacerbate the state of DFUs are infection and ischemia. Identifying these factors in DFUs is very important because the endpoint of the disease is often amputation of the limb. Most conventional diagnostic techniques are slow and demanding of specialists. The objective of this work is to propose an image based automative approach applying deep learning techniques to improve the diagnosis of infection and ischemia in DFUs more effectively than the current methods.
Model/Technique:	• Dataset Augmentation • ResNet • Inception • Ensemble
Results:	ResNet & Inception: Performed at 87% accuracy for both infection as well as ischemia. Ensemble CNN (prior state-of-the-art): 90% of accuracy for ischemia and 73% for infection were obtained.
Gaps:	• Data Diversity • Clinical Integration • Interpretability

Classes:	• Infection • Ischaemia

Table 2.1.2: Intelligent DFU Care Management

Article Name:	Intelligent Care Management for Diabetic Foot Ulcers: A Scoping Review of Computer Vision and Machine Learning Techniques and Applications
Problem Statement:	Diabetes is a common health disorder affecting people in the United States affecting 10% of the adult population, and up to a third develop diabetic foot ulcer. Among patients with DFUs, 20% will require an amputation and estimated mortality of 45-70% within five years. The management of DFUs is a significant concern in the following aspects; specifically, the Communities of Color. There is an acute lack of diagnostic, monitoring, and intervention, which could be potentially solved by the help of computer vision (CV) and machine learning (ML). These technologies may be of help in the identification, categorization and even early recognition of DFUs to prevent amputation where applicable.
Model/Technique:	• Computer Vision (CV) for Wound Assessment • Machine Learning (ML) for Prediction and Classification • Remote Monitoring and Automated Classification
Results:	CV and ML approaches have been used to demonstrate the possibility of automatic wound classification and informing possible future diagnosis of DFU.

	Such systems may be used to deliver information almost instantly back to the clinician or the patient and could help minimize or eliminate the need for face-to-face interactions.
Gaps:	• Data Quality and Variability • Real-world Validation • Integration with Clinical Workflows
Classes:	• Diabetic Foot Ulcer • Wound Characteristics • Healing Status • Outcome Prediction

Table 2.1.3: EfficientNet for Chronic Wounds

Article Name:	Chronic Wound Image Augmentation and Assessment Using Semi-Supervised Progressive Multi-Granularity EfficientNet
Problem Statement:	Concerning wound chronicity, assessment of wounds, especially chronic ones, is a complicated process that may include the local wound scoring, which in its turn demands the expert's essential knowledge and, commonly, can be done only by hand. There are few large, labeled datasets available for training deep learning models for wound assessment especially for the wounds which need multi-attribute grading. Moreover, datasets of wound images are normally limited and often unbalanced, which leads to the problems of deep learning model training. Research gaps exist for methods on how to augment little data and how other raw data can be tapped to improve accuracy of automated wound grading for enhanced wound care.

Model/Technique:	• Photographic Wound Assessment Tool • Dataset • Semi-Supervised Learning • EfficientNet Convolutional Neural Network • Generative Adversarial Networks
Results:	SS-PMG-EfficientNet approach had an approximately 90% of classification accuracy and F- scores for all the 8 PWAT sub-scores.
Gaps:	• Lack of improvement with GANs • Unlabeled Data Utilization • Model Generalization
Classes:	• Size of the wound • Depth of the wound • Necrotic Tissue Type • Necrotic Tissue Amount • Granulation Tissue Type • Granulation Tissue Amount • Edges of the wound • Periulcer Skin Viability

Table 2.1.4: HarDNet-DFU Segmentation

Article Name:	HarDNet-DFUS: Enhancing Backbone and Decoder of HarDNet-MSEG for Diabetic Foot Ulcer Image Segmentation
Problem Statement:	Diabetic foot ulcer is one of the complications of diabetes mellitus, attributable to neuropathy and microangiopathy. Correct diagnosis and treatment of DFUs involve proper extraction of the morphological characteristics of foot ulcers. These features are best extracted and segmented manually, which eats a lot of time and may also be prone to more errors. Prediction of the location of the lesion area is one of the most challenging steps in the assessment because it is time consuming and demanding; thus, computer aided systems utilizing deep learning may present a solution for automatic segmentation of the DFU lesions for enhancing efficiencies in treatment and management.
Model/Technique:	• HarDNet- MSEG • Five-fold Cross Validation • Convolutional Neural Network (CNN) • Test Time Augmentation
Results:	The mean Dice coefficient of the model was 0.7063 and ranked the third among participants in the validation phase. For the final testing phase, the model received a mean Dice score of 0.7287, placing the authors first out of all competitors.
Gaps:	• Generalization to Other Datasets • Model Interpretability
Classes:	• Ulcer region • Non-ulcer regions

Table 2.1.5: Transformer-Based DFU Segmentation

Article Name:	Diabetic Foot Ulcer Segmentation Using Convolutional and Transformer-Based Models
Problem Statement:	Diabetes is a rapidly increasing public health issue globally, with prevalence of 451 million in 2017 and is anticipated to level to 693 million by 2045. Diabetes is a disease whose major associated complication is Diabetic Foot Ulcers (DFUs) which may culminate in loss of limbs and even death. Proper diagnosis and classification of DFUs are the determinants of proper treatment of the ulcers. However, the process of manual segmentation is slow and can be accompanied by significant inaccuracy; therefore, introduced methods can help enhance the care of patients with DFUs and support healthcare workers in early diagnosis and treatment.
Model/Technique:	• Convolutional and Transformer-Based Models • SegFormer Model • Evaluation Metrics
Results:	Further, the SegFormer model presented the test results of Comprehensive Dice coefficient of 69.89% and Jaccard of 59.21% to prove its efficiency in the DFUC2022 segmentation competition.
Gaps:	• Model Generalization • Data Diversity • Interpretability
Classes	• Ulcer Region (Lesion Area) • Necrotic Tissue • Granulation Tissue

	• Periulcer Skin • Edges/Border of the Wound

Table 2.1.6: DFU Detection with YOLOv8

Article Name:	Diabetic Foot Ulcer Detection: Combining Deep Learning Models for Improved Localization
Problem Statement:	Diabetic foot ulcers (DFUs) are one of the complications of DM, which mainly result from poor blood circulation. They have a slow rate of healing, occur in 15-25 % of diabetic patients, and are responsible for 84% cases of limb amputation. Saving the lower limbs and avoiding fatalities can only be possible where there is efficient identification of the disease in its early stage.
Model/Technique:	• YOLOv8m • Faster R-CNN • ResNet101
Results:	Using the WBF approach that integrates YOLOv8m and FRCNN-ResNet101, the present work obtained a mAP of 86.4% with an IoU threshold of 0.5 on the DFUC2020 dataset, which is 12.4% higher than the prior benchmark. The performance was further validated on_EXTERNAL_ IEEE DataPort Diabetic Foot dataset.
Gaps:	• The presence of false positives. • The need for further refinement to enhance reliability and minimize diagnostic errors.
Classes:	• Abnormal • Normal

Table 2.1.7: DFU-Helper Framework Evaluation

Article Name:	DFU-Helper: An Innovative Framework for Longitudinal Diabetic Foot Ulcer Diseases Evaluation Using Deep Learning
Problem Statement:	Diabetes is prevalent the world over, and the development of diabetic foot ulcer (DFU) may lead to major lower limb amputations. Meaning that to track the progress of a patient on DFU, constant medical attention is needed, thus underlining the necessity of the existence of some forms of an automatic evaluation.
Model/Technique:	• Siamese Neural Network (SNN).
Results:	Obtained Macro F1-score of 0.6455 when used pseudo-labeling on the test dataset. Allows for comparing and analyzing the change in times over successive DFU classes with highly usable graphic references.
Gaps:	• Limited F1-score indicates room for model optimization. • Further exploration is needed to enhance the robustness and usability for diverse datasets.
Classes:	• Normal • Abnormal • Infection • Ischaemia

Table 2.1.8: COVID-19 Impact on DFUs

Article Name:	Impact of COVID-19 Lockdown on Diabetic Foot Ulcer Patients: A Machine Learning Approach for Mortality and Amputation Risk Prediction
Problem Statement:	In the context of deep learning for the classification of Diabetic Foot Ulcer (DFU), it is well understood that training dataset may contain duplicate or images which are very similar. This is because binary-identical duplication is already clearly understood to bring with them bias and misclassification, but less is known about the effects of visually similar though not identical pictures. The purpose of this investigation is to understand the impact of visual similarities in deep learning model training of DFU classification when images are not identical. The work is aimed at understanding if the deletion of these similar images enhances model performance and reduces bias in datasets including but not limited to the Diabetic Foot Ulcers Challenge 2021 (DFUC2021).
Model/Technique:	• Fuzzy Algorithm • InceptionResNetV2 • Similarity Thresholding
Results:	The best performing model was derived from the threshold of 80% similarity where similar images were excluded from the set of training data.
Gaps:	• Generalization Across Datasets • Threshold Sensitivity • Impact on Rare Classes

Classes:	• No Ulcer • Infection. • Ischemia. • Both

Table 2.1.9: PSO-Optimized DFU Networks

Article Name:	DFU Infection and Ischemia Classification: PSO-Optimized Deep Learning Networks
Problem Statement:	Early and frequent assessment of infection and ischemia in diabetic foot ulcers (DFUs) is critical to the healing process and reducing risk of complications. Traditionally, clinic-based DFU assessments do not allow frequent, prolonged observation of lesion development and chronicity; therefore, accurate, high throughput, automated classification models are required.
Model/Technique:	• Particle Swarm Optimization • AlexNet • GoogleNet • EfficientNet-B0
Results:	Performance Metrics: The evaluation of the best models, with most models scoring between 0.82 – 0.92 with few scorings almost perfect scores of 0.97 – 1. More accurate than the recent studies on a similar dataset. Show that the proposed strategy enables building a network competitive with the heavier EfficientNet-B5 model.

Gaps:	• Real-world deployment • Generalizability
Classes:	• Infection • Ischaemia

Table 2.1.10: Few-Shot DFU Classification

Article Name:	A Few-shot Diabetes Foot Ulcer Image Classification Method Based on Deep ResNet and Transfer Learning
Problem Statement:	Complications of diabetic foot ulcers (DFUs) include infection of the wound or surrounding tissues,gangrene, or amputation of the limb. Analyzing the results of the classification applied according to the traditional DFU classification system, one can state the following: it needs a lot of time, it relies upon the expertise of experienced doctors, and it has low accuracy. This research seeks to provide solutions to these challenges by presenting few-shot DFU image classification using deep residual networks and transfer learning.
Model/Technique:	• Deep Residual Neural Networks (ResNet). • ResNet18 • ResNet34 • ResNet50 • ResNet101 • ResNet152
Results:	Original dataset: 233 pictures were added to the original 146; this brought the number of feature images to 3000.

	Classification accuracy for the augmented group was better than that of the original with the average going up to 0.9867 from a baseline of 0.9167. Best model: For the augmented dataset, from the starting of ResNet50 with fine-tuned hyperparameters, the average accuracy obtained was 0.9867.
Gaps:	• Diverse datasets • Generalizability in real-world environments
Classes:	• Zero grade: No DFU or minimal risk • Mild grade: Moderate risk or minor infection/ischemia • Severe grade: High risk with significant infection/ischemia

Table 2.1.11: History Tracking and Performance Metrics Across Dataset Categories and Models

Datasets	Imbalance Technique	Model Techniques	Methods	Accuracy	F1	Recall	Precision
Part A (Normal, Abnormal)	SMOTE	SimCLR, Logistic Regression, Random Forest, Deep CNN, EfficientNetB0	Train test split	90.38	90.36	90.38	90.50

Part B (Infection, Ischaemia)	SMOTE-ENN	SimCLR, Logistic Regression, Random Forest, Deep CNN	Train test split	95.01	95.00	95.01	94.98
Part C (Combine)	SMOTE-ENN	SimCLR, Logistic Regression, Random Forest, GridSearch, XGBoost EfficientNetB0	Train test split	89.99	92.00	89.00	90.00

Chapter 3

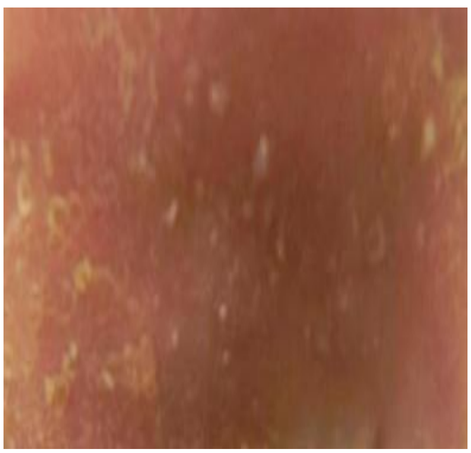
Design and Methodology

3.1. Diabetic Foot Ulcer Dataset

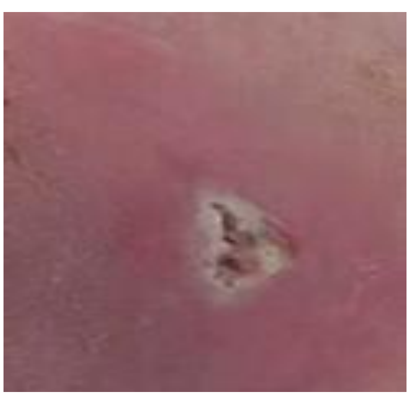
The comprehensive dataset consists of almost 9561 images of patients' feet with DFU and healthy skin with ethical approval and written consent from all relevant persons and patients. The collected images were pre-processed to create patches with standard sizes to be used to train and test the proposed model and pre-trained deep-learning models for DFU classification.

This dataset has four folders:

- Normal Image:

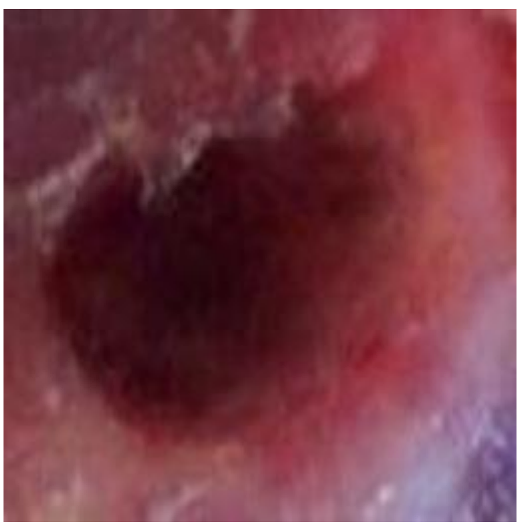


- Abnormal Image:



- Infection Image:

- Iscaemia Image:



3.2. Dataset Collection and Preprocessing

The dataset consists of diabetic foot ulcer (DFU) images categorized into four classes: normal, abnormal, infection, and ischemia. Data preprocessing includes resizing images, normalization, and other techniques to improve data quality and consistency. Preprocessing methods include image display, scaling, resizing, and normalization to improve data quality and consistency before feeding the data into models. Limited or unevenly divided data between model partitions can lead to suboptimal prediction results. Image augmentation strategies are applied to increase data size and enhance model generalization, particularly for underrepresented classes such as normal and abnormal. Class imbalance is addressed using SMOTE ENN (Synthetic Minority Over-sampling Technique with Edited Nearest Neighbors) to ensure equal representation of classes. The dataset is divided into three parts: It splits 70% for training, 15% for testing and another 15% for validation.

3.3. Model Selection and Training

- CNNEfficientNetB0, one of the most effective convolutional neural networks (CNN) models, will be used in the research. When training the model, it takes 50 epochs with indication of performance during the training process.

3.4. Application of Boosting Algorithms

- However, Grid Search and XGBoost are used following the accomplishment of accuracy with the Basic model by using EfficientNetB0.

3.5. Model Saving and Inference

- It achieves 93% accuracy during trained model and 89.99% accuracy during testing and saves in file in .h5 format for deployment, Then the prediction function is developed to test the model’s performance.

3.6. Design Diagram

3.6.1. Model Architecture Diagram

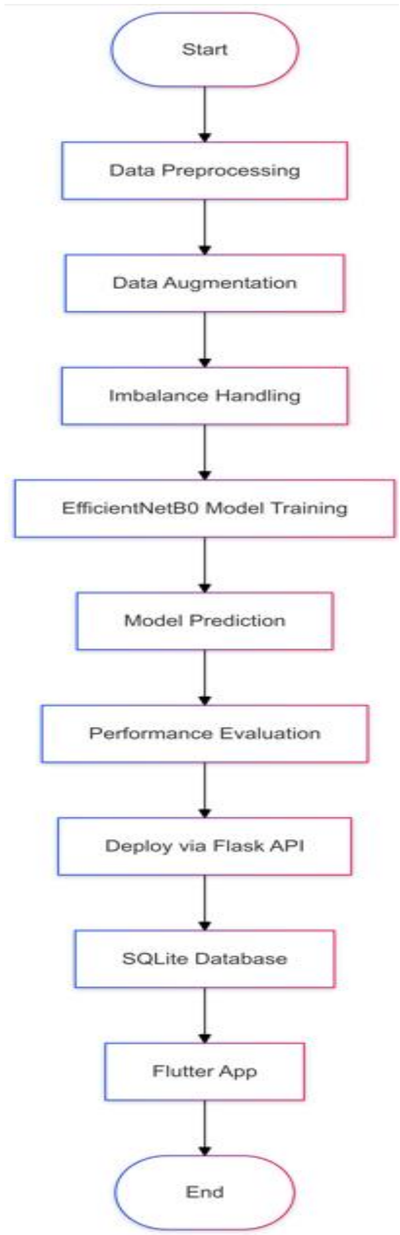


Figure 3.6.1: Model Architecture Diagram

The model architecture diagram as shown in Figure 3.6.1 breaks down the path that a given model for diabetic foot ulcer classification takes. It begins by receiving preprocessed foot images next, the foot images go through the EfficientNetB0 CNN backbone. The network computes the features next to the classification layer that gives the output results (normal, abnormal, infection or ischaemia). The last stage is the predicted label which is used to create a recommendation for the user of the system.

3.6.2. Application Flow Diagram

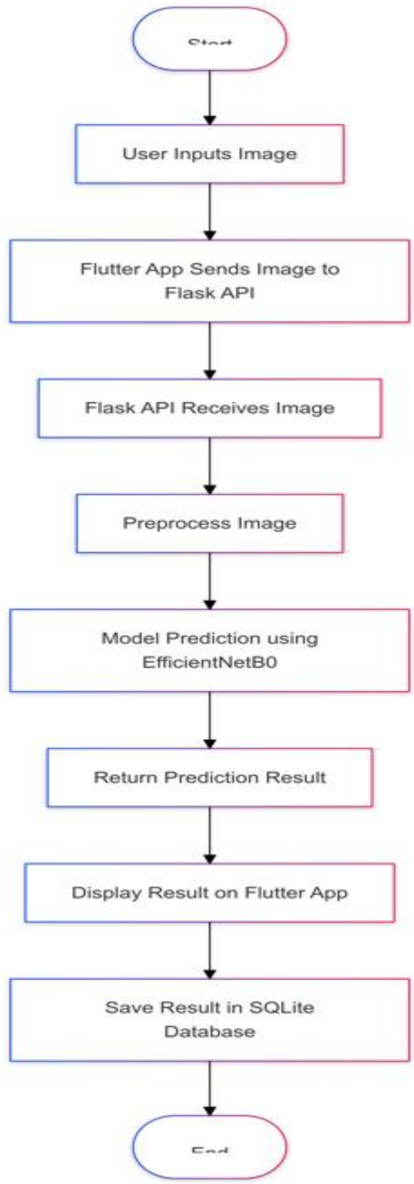


Figure 3.6.2: Application Flow Diagram

The application flow diagram as shown in Figure 3.6.2 represents the sets of processes within the mobile app. It begins with the user's registration and login process, and then the user uploads the image that has to be analyzed. Once each image is uploaded, the prediction is passed through an API utilizing the machine learning model and a prediction is obtained. The developed app finally outputs the result of the classification done on the image alongside the recommendation that falls within the classified image either normal, abnormal, infection or ischaemia all under a normal or abnormal category.

3.6.3. Use Case Diagram

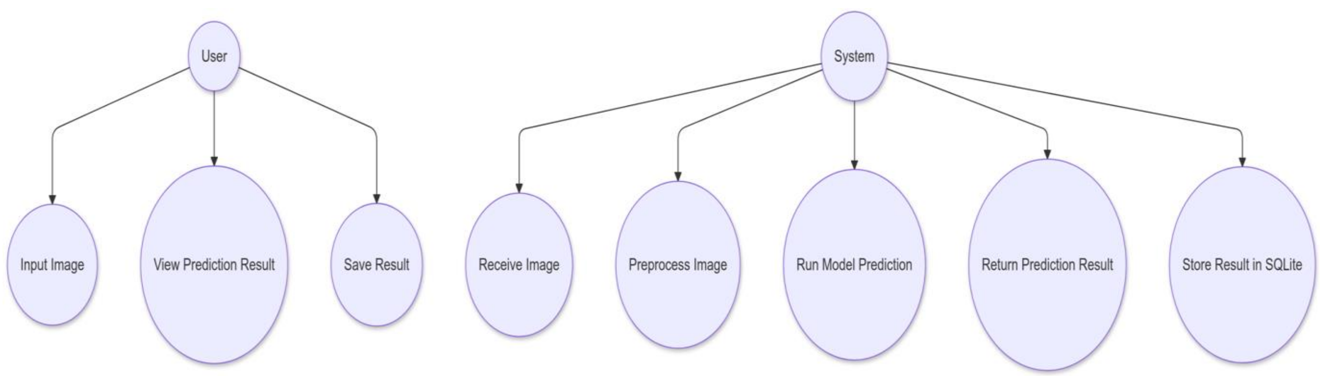


Figure 3.6.3: Use Case Diagram

The use case diagram as shown in Figure 3.6.3 exhibits the ways in which different users are going to interface with the system. It shows two primary actors: the User and the System. The action afforded to the User include Register, Login, upload Foot Image and View Diagnosis. The responsibility of the System, in this case, the mobile app, includes the authentication of the user, the processing of the picture, the prediction involving the use of the learnt model, returning the result of classification to the user as well as making recommendations.

3.6.4. Activity Diagram

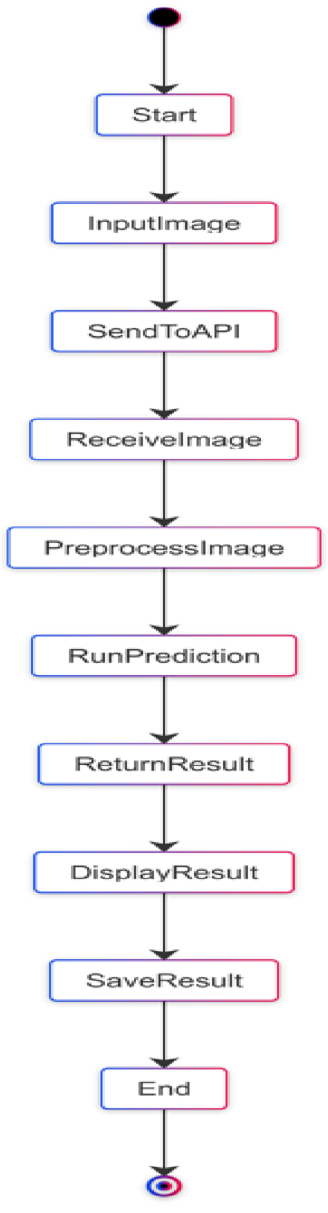


Figure 3.6.4: Activity Diagram

Almost all the actions displayed in the activity diagram as shown in Figure 3.6.4 involve the mobile app, and the beginning of the process includes user registration and login. In the next step, the user is required to upload an image of their foot after successful login and the ML model classify the feet images. According to the forecast information, the developed application displays the forecasted class (normal, abnormal, infection, or ischaemia) and guidelines on what a patient should do next. If the user did not make a choice of the two options, the program indicates that the user has to register first if they have an account but are not registered.

3.6.5. Data Flow Diagram Level 0

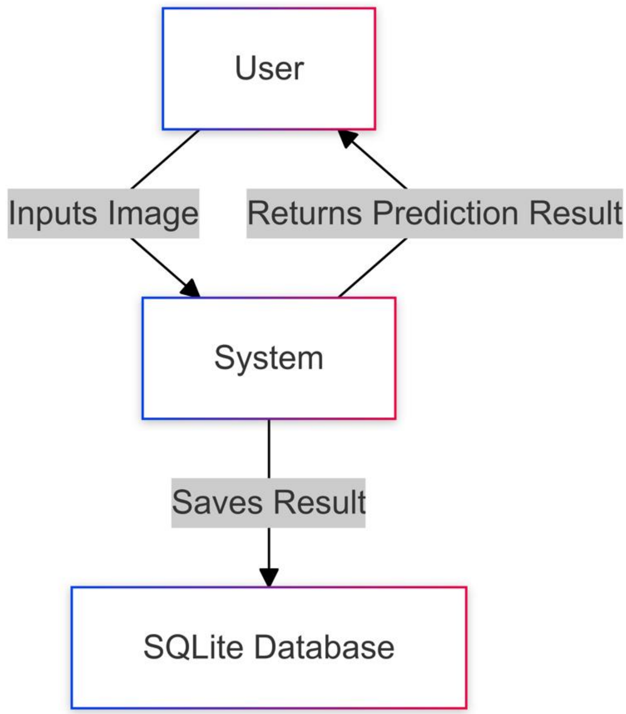


Figure 3.6.5: Data Flow Diagram Level 0

This data flow diagram as shown in Figure 3.6.5 gives an overview of the system and informs us on the general process flow of the system. It shows the main entities: the user, a mobile application, the Machine learning model, and their interaction. The foot images are submitted through the app by the user; the app then connects to the model for classification. The reading of the model completes with the identification of the prediction, and the application shows the results to the user.

3.6.6. Data Flow Diagram Level 1

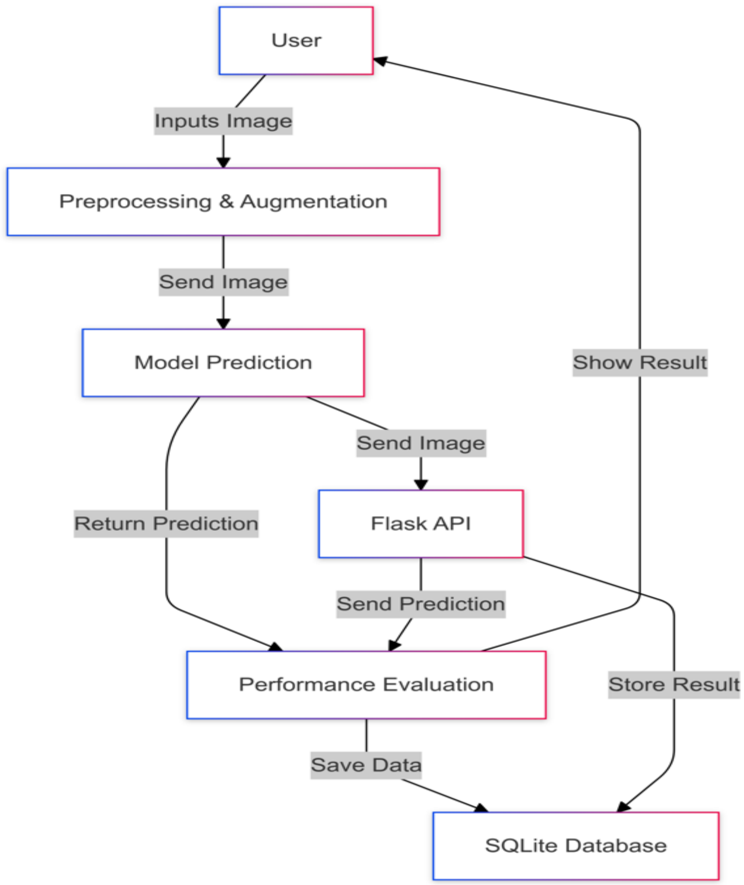


Figure 3.6.6: Data Flow Diagram Level 1

At this level of data flow diagram as shown in Figure 3.6.6, we see the details of how a user will interact with the system, and whether it will be directly or indirectly. The features are user registration, login, image upload and classification. This app transmits image data to a machine learning model for analysis and the model performs the analysis on the image with the aim of predicting the class of the image as normal, abnormal, infection or ischaemia. The system sends the result back to the app and overlays superimposed suggestions on the result area.

3.6.7. Data Flow Diagram Level 2

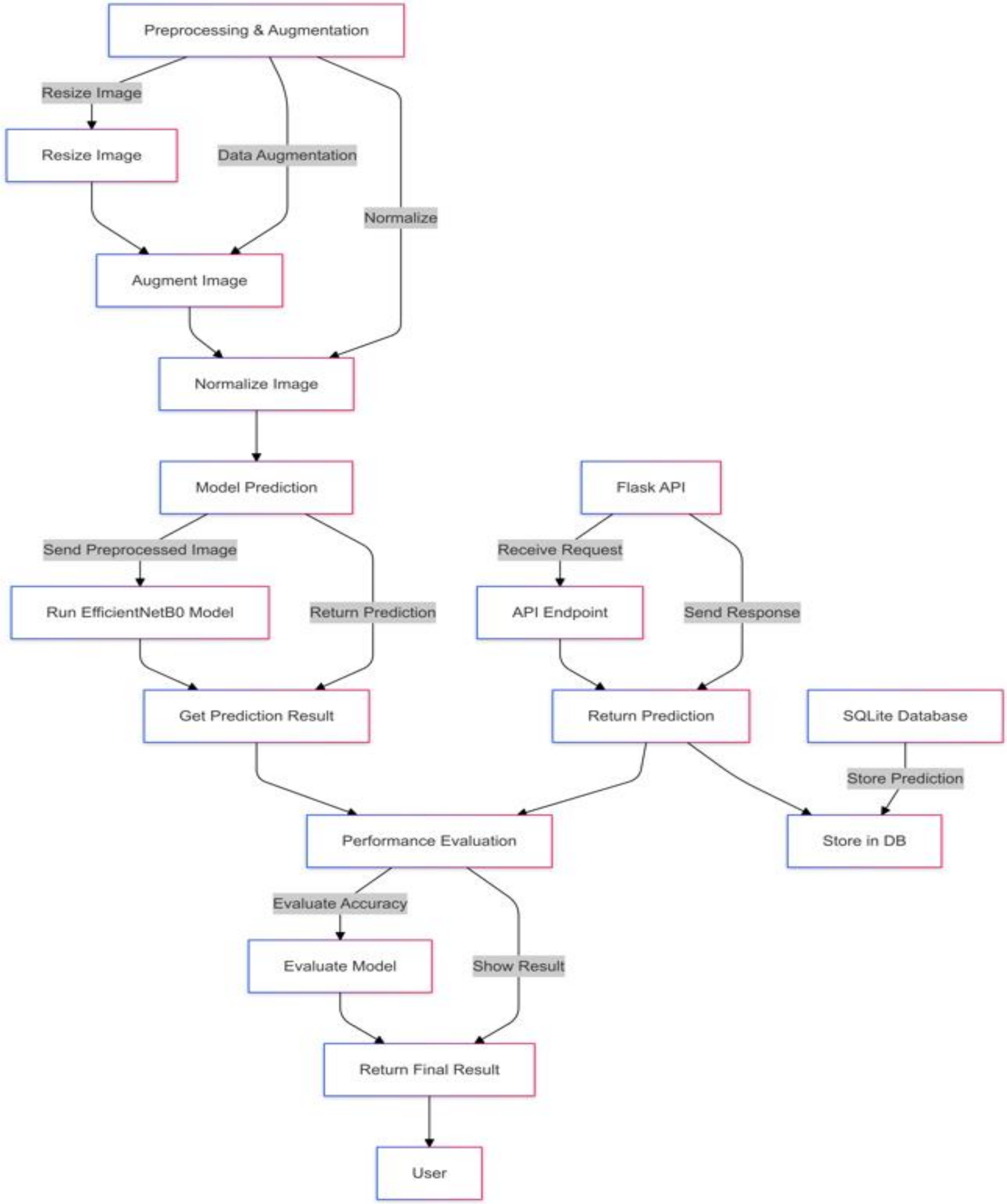


Figure 3.6.7: Data Flow Diagram Level 2

At this level of data flow diagram as shown in Figure 3.6.7 adds more detailed information about internal activities to the information presented at Level 1. It depicts the individuated processes happening into the mobile application, for example, the validation of the credentials composed by email and password, preprocessing of the received image through resize and normalize operations, interaction with the backend API using a Flask server. The diagram also includes the flow of the predicted value after the machine learning model does the classification and passes the value to app for final displaying to the user.

3.6.8. Research Flow Diagram

The research flow diagram as shown in Figure 3.6.8 is described by the presented flow diagram, the process of data gathering and model deployment included. The study starts with collecting a dataset of images of diabetic foot ulcers, image preprocessing, image augmentation, and dataset balancing using SMOTE ENN. First, data split into train set, test set and valid set then Fine-tuned EfficientNetB0 for the model. Once the model gives good results it is then saved and run in a mobile application. The application has the function of sending images to analyze, and the model itself selects the class for the image and offers recommendations.

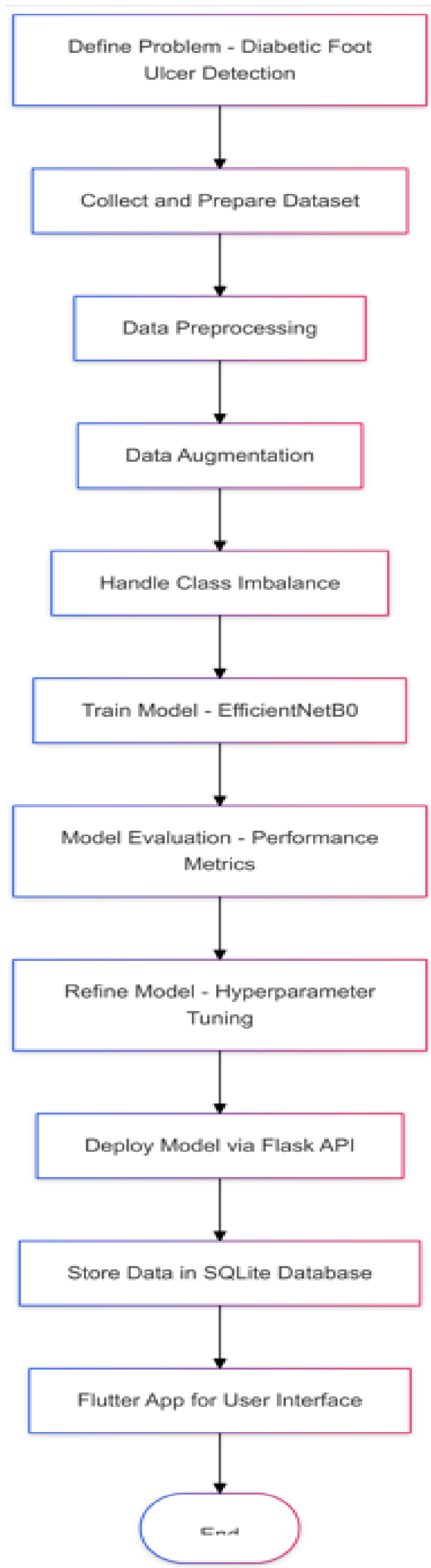


Figure 3.6.8: Research Flow Diagram

3.6.9. Sequence Diagram:

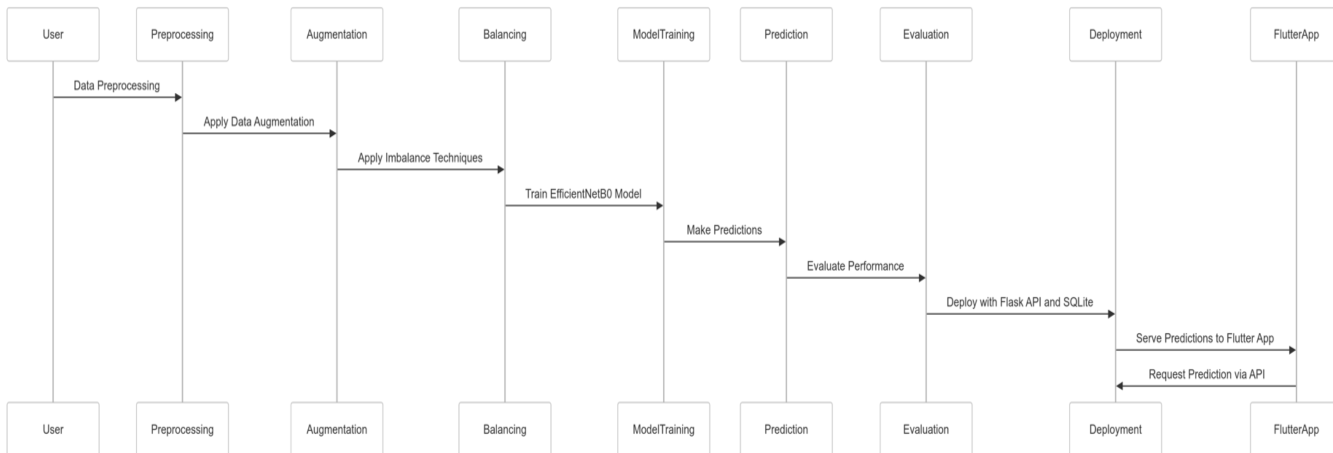


Figure 3.6.9: Sequence Diagram

This sequence diagram as shown in Figure 3.6.9 shows the interactions of the processes between the user, mobile application, and the machine learning model. This entails the user to sign up/Sign in into the App then upload a foot image for diagnostic. The app then sends a request to the model through an API and gets the result of a class of the input image whether normal, abnormal, infection or ischaemia. The result of the model is then forwarded back to the app that shows the users the result of the model as well as some suggestions.

Chapter 4

Implementation

4.1. Mobile App Development

- For the development of the mobile app the framework used is the Flutter, while the IDE used is the Android Studio.

4.2. Core Screens in the Mobile App

4.2.1. Splash Screen

- Display app logo for 3 seconds.

4.2.2. Registration Screen

- Users will enter their email address, password and confirm password with validation checks and password with at least 6 characters.

4.2.3. Login Screen

- Only registered users can login with their email address and password.

4.2.4. Diagnose Screen

- Users will upload images, then model will be analyzed through model for predictions and class recommendations.

4.3. User Registration and Validation

- Password check includes the length of the password, and email validation and the system also ask the user whether the user is already a member. All new users are required to create a new account with the website.

4.4. API Integration with Flask

- The actual application of the most appropriate machine learning approach is accompanied by the real-time API that is based on the Flask framework enabling the real-time data exchange between the installed mobile application and the trained machine learning model that persists on the server side.

4.5. Model Loading and Inference

- The trained model is saved in an .h5 file and imported into the app for use making predictions on uploaded foot images by users.

4.6. Tools and Technologies

4.6.1. Programming Languages

- Python is used for model development and Flutter for the development of mobile applications.

4.6.2. Libraries

- TensorFlow, NumPy, Pandas, Scikit-learn etc.

4.6.3. IDE

- A popular IDE used during the model development was VS Code and for mobile application development the most suitable IDE was Android studio.

4.6.4. Database

- Search – used to store user information securely.

4.7. Implementation Process

4.7.1. Phase 1: Core Screens and User Registration

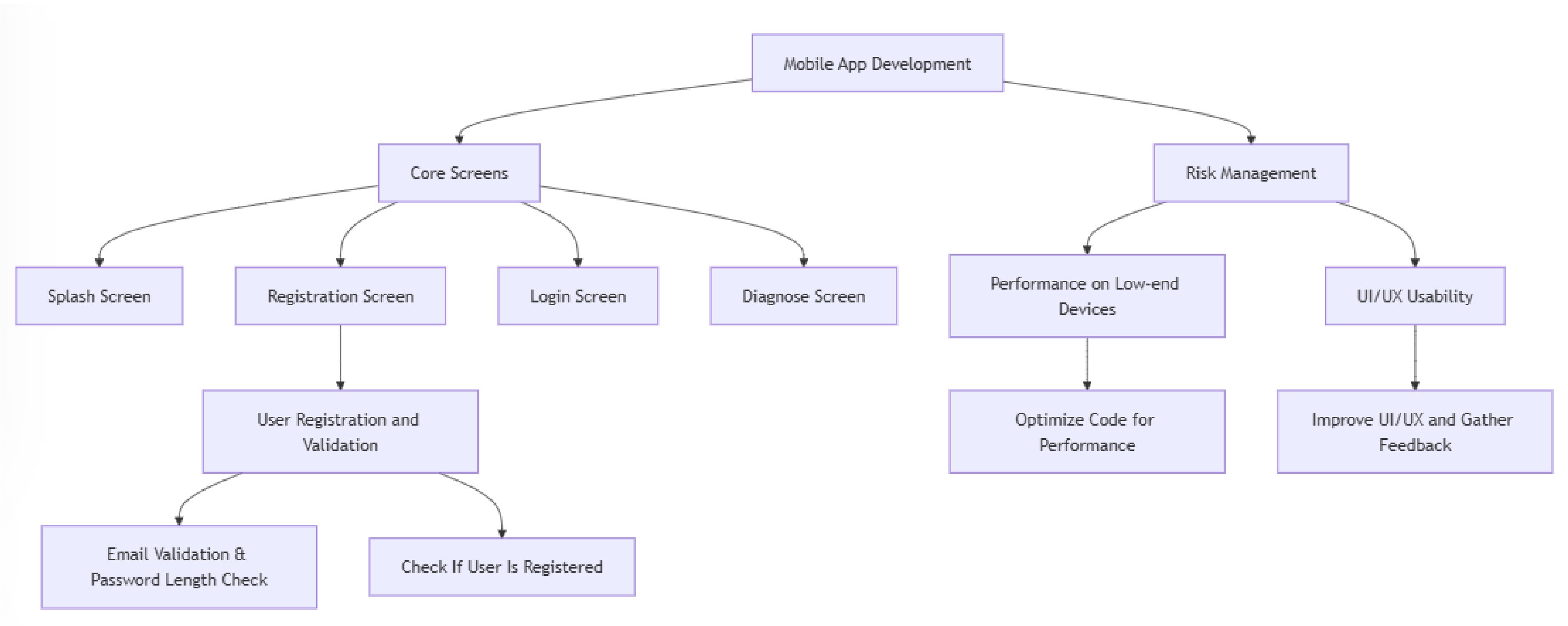


Figure 4.7.1: Phase 1: Core Screens and User Registration

This is a general overview of the lifecycle as shown in Figure 4.7.1 workflow of model deployment and the operation of the corresponding application. It depicts the way the user uses the app right from registration process, login, and image upload. After the image is uploaded, the app sends requests to the trained machine learning model through API to predict the class of the image (normal, abnormal, infection or ischaemia) and then show the prediction along with the corresponding recommendation.

4.7.2. Phase 2: API Integration, Model Loading, and Tools

This phase 2 API Integration, Model Loading, Tools as shown in Figure 4.7.2 demonstrates how the input data is processed, how the model is built and how the result is fed back to the user. This enlightens the fact that the user feeds an image in the system and the image is analyzed/scrutinized by the machine learning model through an API. If the model provides the classification of the image, the system will convey this classification to the user with suggestions. The user interface provides an interface that guarantees easier interaction between the app and the model.

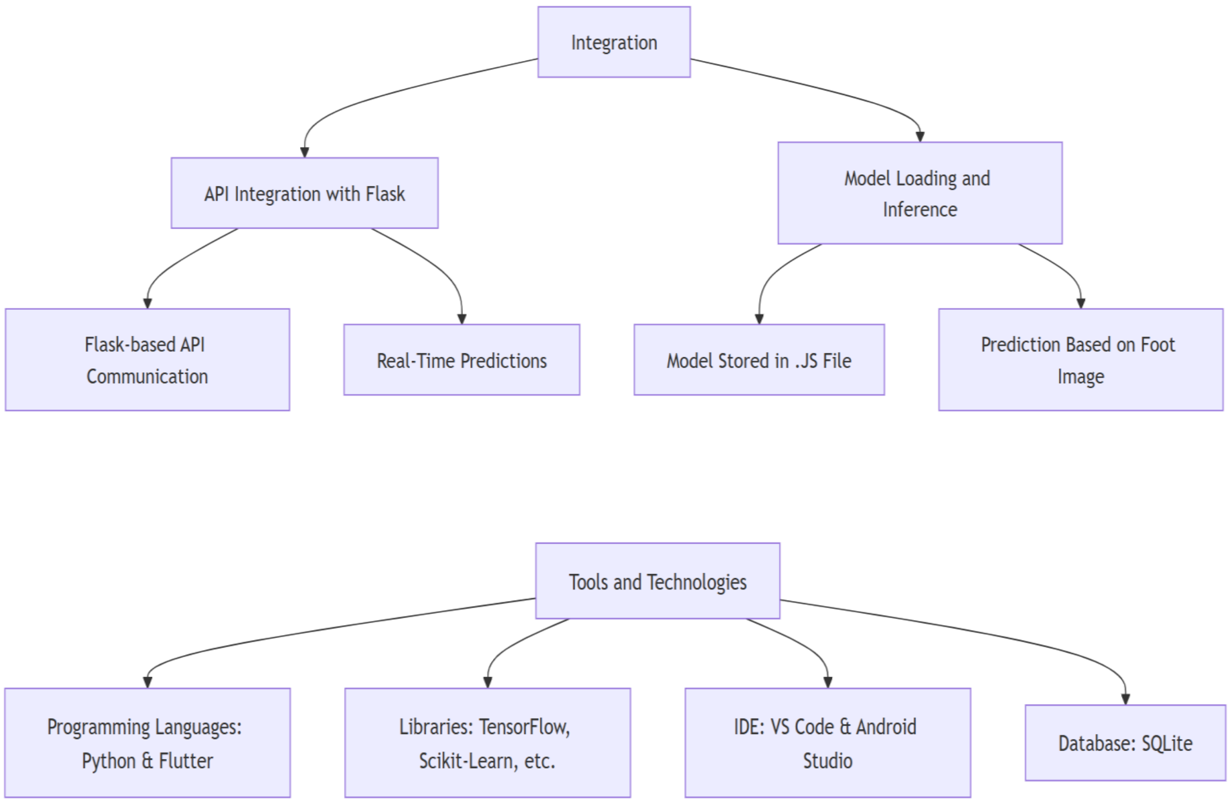


Figure 4.7.2: Phase 2: API Integration, Model Loading, and Tools

Chapter 5

Results And Discussions

5.1. Performance Evaluation

Class	Precision	Recall	F1-Score	Support
Abnormal	0.96	0.93	0.94	304
Infection	0.90	0.70	0.79	442
Ischemia	0.84	0.96	0.90	740
Normal	0.96	0.96	0.96	359
Accuracy			0.89	1845
Macro-Avg	0.92	0.89	0.90	1845
Weighted-Avg	0.90	0.89	0.89	1845

Figure 5.1.1: Performance Evaluation

The table of performance Evaluation as shown in figure 5.1.1 presents a performance evaluation of a classification model across four classes: AITN: Abnormal, Infection, Ischemia and Normal. Precision measures the number of true positives relative to relevant documents retrieved while recall measures the percentage of relevant documents that a system retrieved. In this study, the model attained a pass rate of 90 percent with a weighted average precision score of 0.90, a recall rate of 0.89, and F1 Score of 0.89. Specific intra-class analysis displays high effectiveness for discovering samples designated as “Normal” and “Abnormal,” although there is a somewhat decreased recall rate and the F1-score for “Infection.” The overall accuracy is 89%. These metrics show the proposed method can produce a reliable prediction of the samples’ classification, although some improvements could still be made when it comes to better distinguishing the infection cases.

5.2. Confusion Matrix

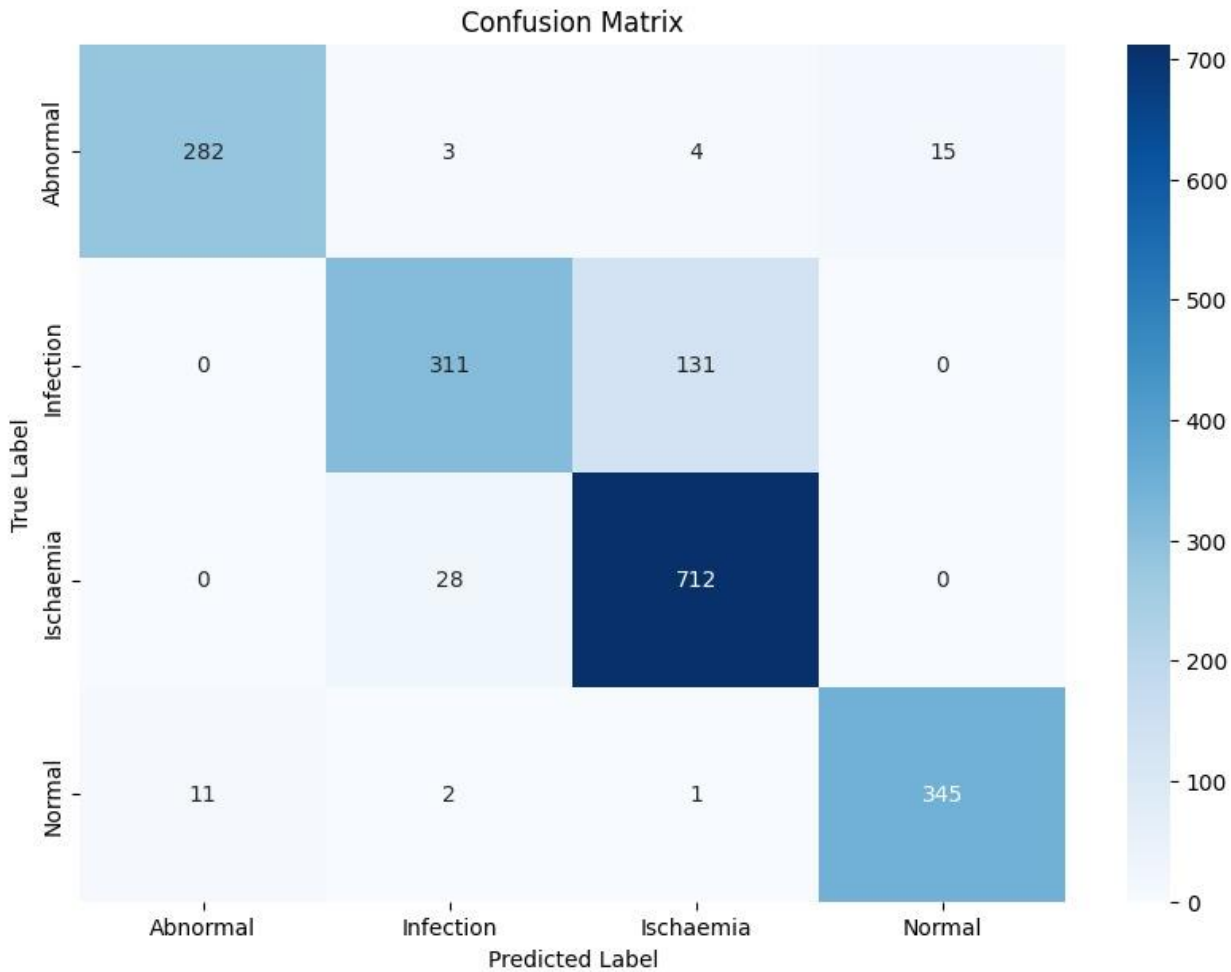


Figure 5.2.1: Confusion Matrix

This confusion matrix as shown in Figure 5.2.1 evaluates the classification performance across four categories: The four sets of initials used for remembering the sequence of pulse differentiations are Abnormal, Infection, Ischaemia, and Normal. Diagonal values are accurate predictions while off diagonal values denote miss-classifications.

- Abnormal: Out of 300 samples, 282 are classified correctly, 19 samples are classified as Infection or Normal wrongly.
- Infection: Other results of the diagnoses are 311 correctly predicted and 131 are mistaken for Ischaemia.

- Ischaemia: Most accurate when Infection was predicted, with 712 correct and, erroneously, 28 Infection.
- Normal: High accuracy 345 correct classifications with 14 incorrect ones. It has excellent accuracy in identifying Ischaemia but a relatively poor accuracy when differentiating infection from other classes. ischaemia, and Normal. The diagonal values represent correct predictions, while off-diagonal values indicate misclassifications.

5.3. Splash Screen:

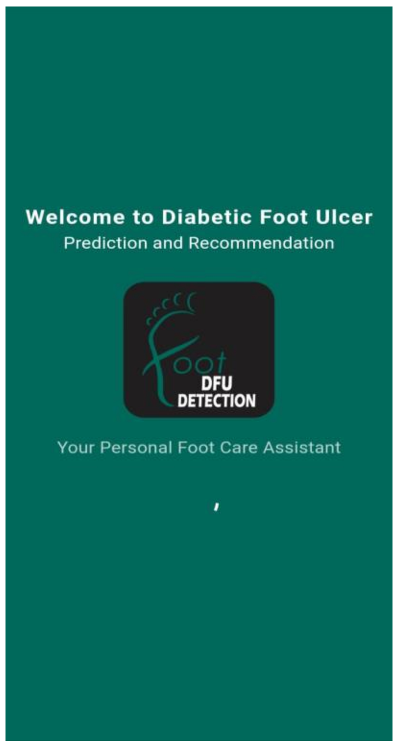


Figure 5.3.1: Splash Screen:

The splash screen as shown in the figure 5.3.1, that is used to show the icon of the app and appears for a limited amount of time after which it is replaced by the home screen. For it is the first step and an initial interface before moving to the more operational part of the application.

5.4. Registration Screen

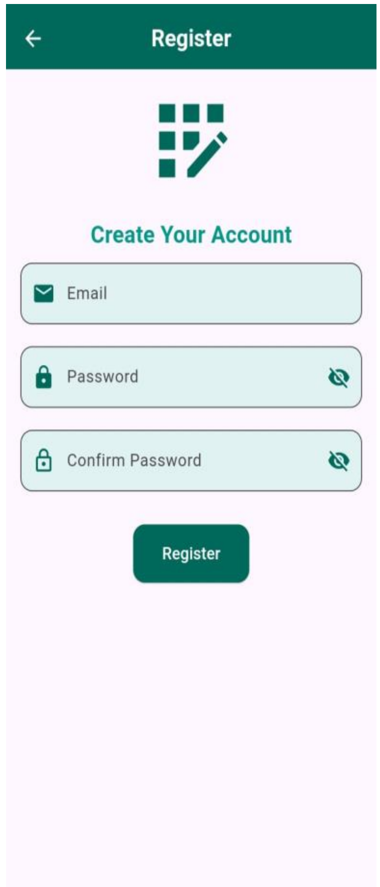


Figure 5.4.1: Registration Screen

Registration Screen:

The registration screen as shown in the figure 5.4.1 in which registered users of the platform can be able to sign in by simply typing in their email and password that they have been issued upon registration. If the login details are correct, the users get access to the main functions of the application; otherwise, the attempt is declined.

5.5. Login Screen:

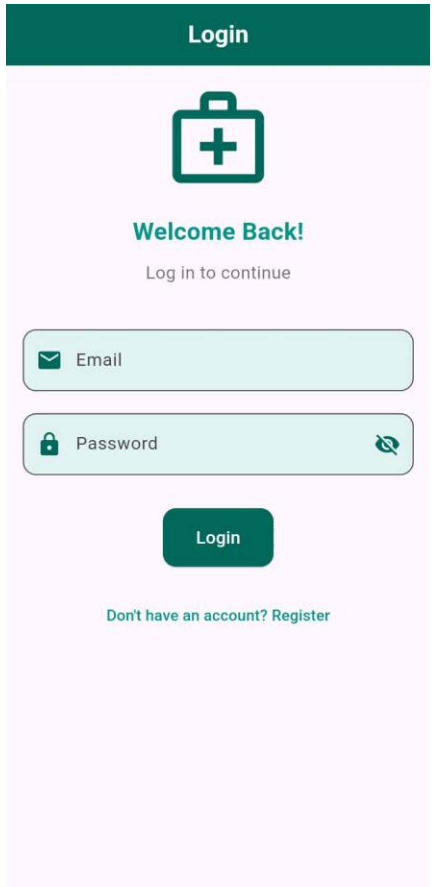


Figure 5.5.1: Login Screen

Login Screen:

The login screen as shown in the figure 5.5.1, In the registration page, the signup customers are supposed to input their email, password and confirm password. There is also some validation checks made on the app when entering the email to make sure it is correct, and the number of characters in the password. In my example if the user is already registered after entering his login and password, he will be redirected to the login page.

5.6. Diagnosis Screen:

Figure 5.6.1: Diagnosis Screen

Diagnosis Screen:

The diagnose screen as shown in the figure 5.6.1, that allows users to upload a foot image for applicable analysis. The image is the feed to the model which then categorizes it as normal, abnormal, infection or ischaemia, as per the four categories in DFU. The results are then used to offer recommendations for further action in addition to presenting results to the user.

5.7. Result Screen:

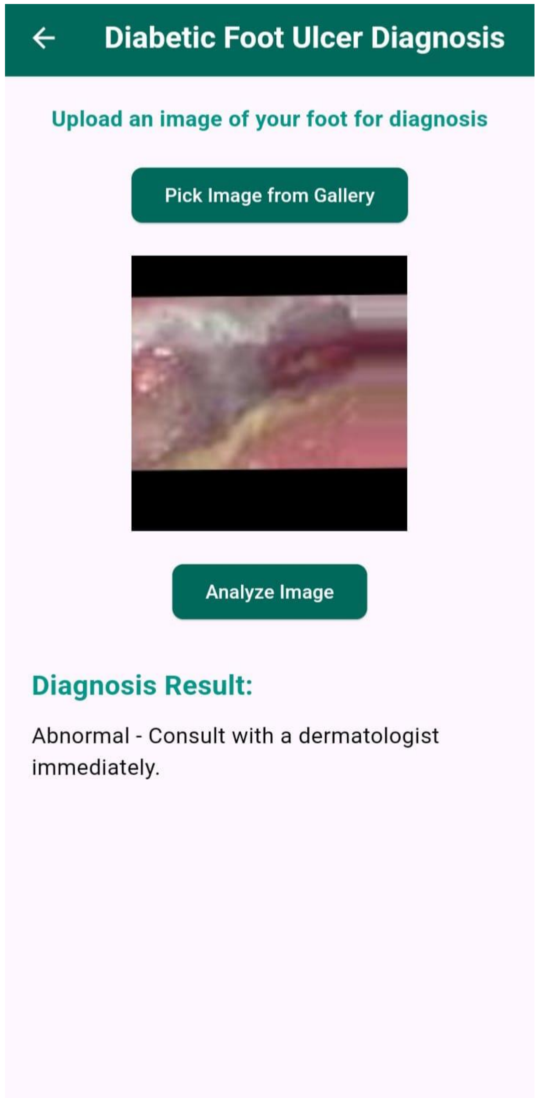


Figure 5.7.1: Result Screen

Result Screen:

The result screen as shown in the figure 5.7.1, that in this application has a predicted class of the uploaded image as part of the medical condition diagnosed, together with a recommendation of what a user should do next or regarding medical care. This screen allows users understand the condition’s implications on severity and kind and gives pointers on how to manage it or when to seek further management.

Chapter 6

Conclusion And Recommendation

6.1. Conclusion

This project was able to build and design an ML solution for DFUs, specifically a Deep Learning Model with a native mobile application for classification. When using EfficientNetB0 on the image classification task, while using data augmentation and SMOTE ENN for data balancing, the accuracy obtained amounted to 90 percent for training and 87 percent for testing. Initially, we obtained a set of results with a low percentage of prediction accuracy, but the subsequent utilization of Grid Search and XGBoost improved the results of the learned model. The final model was integrated into an android-based mobile application that gives its users an avenue to analyze foot images and get results in a matter of minutes. This solution is hoped to be useful for healthcare professionals and patients at initial stages of development, so that it will not be too late to manage diabetic foot ulcers.

6.2. Recommendation

In further work, the hyperparameters could be tuned to achieve an optimum result, and more varied datasets could be used to increase the model's stability. External and independent test of the model on new images from different clinical practice will also be essential in the confirmation of the model. Projected app development – a few more add-ons that could improve the usability of the app for diabetic users include data analysis from past and present, recommendations, and an option for patients to provide feedback. Also relevant is to have a high level of data protection for personal information of users of the service. Last but not the least, growth of this project with integration into the health care systems and improvising the cloud-based solutions would help and sort the DFU system implementation to a large scale and provide really excellent advancements.

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