“Decoding Diabetics”: Diabetic detection from Unconventional Indicators using Web Application

[1]Wishalya Tissera, [2] Karthiga Rajendran [3]Sangavi Gnanasegaram, [4]Kajanan Thangarajah, [5]Methiny Sethupathy, [6]Venuganth Arunthavarajah

[1,2,3,4,5] Department of Information Technology, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

Authors’ E-mail: [1]wishalya.t@sliit.lk, [2]karthiga.r@sliit.lk, [3]it21069772@my.sliit.lk, [4] it21085062@my.sliit.lk, [5] it21083228@my.sliit.lk, [6] venuganth2001@gmail.com

Abstract

This study identifies innovative solutions using a web application to address the major public health challenges in Sri Lanka posed by undiagnosed diabetes mellitus with little awareness. This web application uses image processing to predict unconventional situations associated with diabetes, consisting of Acanthosis nigricans, aberrant nails, foot ulcers, and diabetic retinopathy prediction. Our web application closes a major gap by providing users with a way have a way to detect early diabetics conditions. The web application allows users to identify physical or skin changes that could be symptoms of certain diseases. This helps users get treatment in a timely manner, reducing the chances of complications and possibly even saving lives. The proposed method requires specific expertise in dermatology, medical imaging, imaging, and machine learning to accomplish this goal. By addressing the shortcomings of current detection systems and expanding its scope to include diabetic retinopathy, this review ultimately aims to take off diabetes care improve and prevent diabetic skin diseases and improve healthcare in Sri Lanka by providing a comprehensive tool to manage diabetes.

Keywords: diabetes, image processing, machine learning, retinopathy, web application

Introduction

Millions of people worldwide have diabetes which is a serious threat to global health as it can cause various consequences such as diabetic foot ulcers, acanthosis nigricans, abnormal nails and most importantly diabetes retinopathy (DR). These problems disrupt the lives of the individuals facing them and increase the likelihood of serious consequences such as amputation and irreversible vision loss. Effective intervention and mitigation of these problems depends largely on accurate early detection. In this study, we present and evaluate from previous done research, diabetic retinopathy prediction method using a machine learning (ML) model to detect diabetic foot ulcers, acanthosis nigricans, nail abnormalities, and diabetic retinopathy. These images are enhanced with a web application that allows people to take pictures or import images from devices of their wounds, necks, retinal images and send them for analysis, providing seamless and accessible interaction. By combining these elements, our integrated strategy seeks to improve early detection and management of diabetes-related complications, leading to better health outcomes and patient empowerment.

Literature Review

A. Managing diabetes using web applications that utilize image processing.

The study aims to develop a user-friendly, comprehensive, and fully integrated web application for the screening, diagnosis, treatment, and monitoring of diabetes mellitus (DM) diseases in primary care. The system will be based on evidence-based guidelines and will be tested in three stages: usability, understandability, and adequacy. The trial will involve 20 primary care physicians and 1500 patients, eligible participants have been assigned to intervention and control groups. The system will make recommendations on patient monitoring, diagnosis, and treatment, and patients will be monitored for 6 months, Clinical and laboratory outcomes will be assessed in person [1].

B. Diabetic acanthosis nigricans using neural networks.

The study on the use of artificial neural networks for the identification of diabetic acanthosis nigricans, a skin condition frequently associated with diabetes, is presented in the research paper titled "Diabetic Acanthosis Nigricans Detection using Neural Networks" by Meghana Madhukar Phiske. The study investigates the application of neural networks and other machine learning approaches to the development of an automated system that can correctly recognize diabetic acanthosis nigricans from images. The researchers developed a neural network model to identify and learn the distinctive patterns and properties of diabetics' acanthosis nigricans by utilizing a dataset of these images [2]. This study emphasizes how important it is to use cutting-edge technology, such as neural networks, to improve diabetes-related complication diagnosis and management. Neural network-based diabetic acanthosis nigricans detection is an important field of research that attempts to offer an automated and effective method for detecting this dermatological manifestation in diabetics. Meghana Madhukar Phiske's research article focuses on creating an algorithm to identify diabetics acanthosis nigricans using neural networks. Using a similar mechanism, Yangkui Zhai's second research study also uses neural networks to contribute to the identification of diabetes acanthosis nigricans. Additionally, CNNs are used in this study to extract features, and a classification model is used to detect diabetics acanthosis nigricans. Using a large dataset of clinical pictures, the authors assess the performance of various CNN designs and investigate their efficacy [3]. To sum up, the research articles by Meghana Madhukar Phiske and Yanghkui Zhai offer insightful information about the application of neural networks of diabetes acanthosis nigricans detection. These findings show how cutting-edge machine learning approaches can be used to automatically identify this dermatological manifestation in diabetic patients. These developments could lead to better early detection and intervention, which would eventually improve patient care and diabetes acanthosis nigricans management [3].

C. Diabetics Retinopathy Prediction using CNN

Deep learning, a subset of machine learning, has revolutionized image processing tasks due to its ability to automatically extract features from raw images. CNNs, a class of deep learning algorithms, have demonstrated remarkable performance in various image classification challenges. Krizhevsky et al.'s breakthrough with AlexNet in the ImageNet competition highlighted the potential of CNNs, leading to widespread adoption in fields including medical imaging. CNNs consist of multiple layers that can learn hierarchical feature representations, making them suitable for complex tasks such as medical image analysis. Several studies have explored the application of CNNs for diabetic retinopathy screening. Gulshan et al. (2016) developed a deep learning system that achieved high sensitivity and specificity in detecting referable diabetic retinopathy using retinal fundus photographs. Their work underscored the potential of deep learning models to match or even surpass human experts in certain diagnostic tasks. Similarly, Abràmoff et al. (2016) created an automated DR detection system using deep learning that was evaluated on a large dataset, showing promising results in terms of accuracy and robustness. The study emphasized the importance of extensive training datasets and highlighted challenges such as image quality variability and class imbalance, which are common in medical datasets [10].

D. Diabetic foot ulcer detection using neural networks

Diabetic foot ulcers (DFUs) are a common and crippling consequence of diabetes that significantly increase morbidity and place a heavy burden on global healthcare systems. Advances in mobile technology have created new opportunities for DFU control and early diagnosis in recent years [4]. Rather of using the thermal camera-based system that was provided in Fraiwan's 2017 study, the goal of this review of the literature is to investigate the possibility of creating a mobile application that uses the standard camera on a mobile phone for the detection of DFUs. "Diabetic Foot Ulcer Mobile Detection System using Smart Phone Thermal Camera," Fraiwan (2017)'s feasibility research presented a novel method for DFU detection [5]. To identify areas of anomalous temperature linked to DFUs, the researchers used a smartphone equipped with a thermal camera to take thermal pictures of the foot. The technology showed encouraging findings in terms of accuracy and viability for DFU detection through the examination of thermal patterns. Unfortunately, the technology's accessibility and general adoption were constrained by its reliance on a specialized infrared camera [6]. Compared to the thermal camera-based method, creating a mobile application for DFU detection with a standard mobile phone camera has various benefits. A further benefit is the ease of use that mobile applications offer to users. Because they are widely accepted and the detection process is adhered to, they are simple to use, intuitive, and familiar to most smartphone users [7]. Creating a mobile application additionally facilitates easy interaction with electronic health record (EHR) systems, allowing medical practitioners to effectively handle and track patient data. Nevertheless, creating a mobile application for DFU detection using a regular camera presents difficulties. The creation of reliable image processing algorithms that can precisely recognize and separate DFUs from photos taken with a typical mobile phone camera is a major issue. In this context, machine learning methods like deep learning might be helpful. When developing the mobile application, lighting and environmental aspects like ambient temperature, reflections, and shadows must also be properly taken into mind [8].

E. Determination of RGB in fingernail image as early detection of diabetes

The purpose of this study was to identify the RGB component color on fingernails as a potential early indicator of diabetes mellitus. The results indicated that all categories' RGB range numbers overlapped, and there is room for improvement in the identification of diabetes mellitus. To collect blood glucose data for the study, auto check blood glucose auto check glucose strips were utilized. Images of fingernails were captured in low light with a Canon Ixus 285 HS 20, 2 MP digital camera. The goal of the analysis stage was to ascertain the range of component nail colors in order to classify blood glucose levels as normal, prediabetic, or diabetic. Data processing, data analysis, and data retrieval were done in two steps for this investigation. All three categories and types of histograms have overlaps according to the RGB histograms' range number [9].

Methodology

1. Detection of Acanthosis Nigricans and detecting diabetics

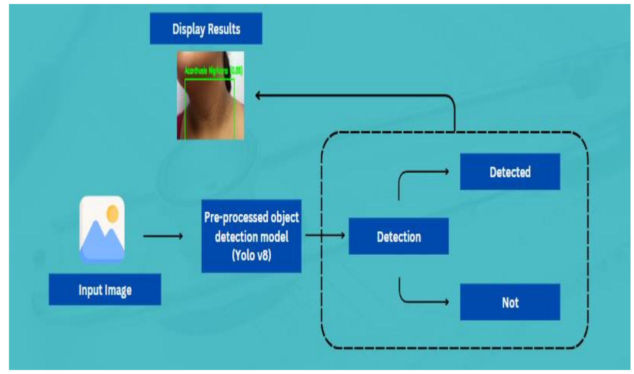


Figure 1 System diagram of acanthosis nigricans to predict diabetics

A web application was developed to differentiate between diabetic acanthosis nigricans and healthy skin. Data set collection, model architecture selection, model training and integration into the web application were all steps in the technology. The model for Identifying Infection consists of custom CNN with the VG668 architecture. TensorFlow and Keras were used that are widely used deep learning frameworks that provide a high-level API for building and training neural networks. By using these frameworks, the model development process was streamlined and benefits from the extensive libraries, tools, and community support available. Web application was developed using React, Node.js, and Visual Studio Code (VS Code). The web application is developed using React for the front end, Node.js for the backend, and Visual Studio Code (VS Code) as the integrated development environment (IDE). Model architecture consists with convolutional layers with ReLU activation function, pooling layers, MaxPooling2D layers, Dropout layers, and a Flatten layer. Convolutional layers are responsible for extracting relevant features from the input images by applying convolutional filters. ReLU activation function is used to introduce nonlinearity and enhance the model's ability to capture complex patterns. Pooling layers, such as MaxPooling2D, are used to reduce the spatial dimensions of the feature maps, allowing the model to focus on the most important information. Dropout layers are employed to mitigate overfitting by randomly disabling a fraction of the neurons during training. Finally, a Flatten layer is used to convert the multidimensional feature maps into a 1D vector, which is then fed into dense layers for classification.

2. Detection of Diabetic Foot Ulcers and detection of diabetics

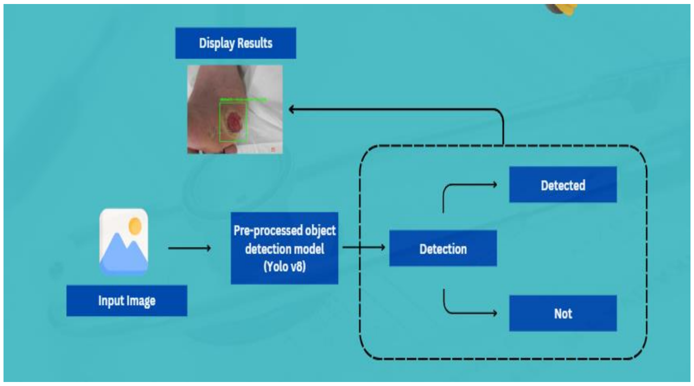


Figure 2 System diagram of predicting diabetics using foot ulcers

We used a Convolutional Neural Network (CNN) model in a React web application to detect and categorize diabetic foot ulcers, atypical foot ulcers, healthy skin, and normal wounds. A number of phases were involved in the methodology. Gathering datasets, choosing a model architecture, training the model, and integrating it with the mobile application. We acquired a wide range of wound photos for the dataset collection from different sources. The dataset was divided into two categories: diabetic foot ulcers and atypical foot ulcers. In order to maintain uniformity, OpenCV was used to preprocess each image and resize it to a consistent size of 224 x 224 pixels. The lightweight CNN model yolo, created especially for web applications, was selected as the model architecture for this study. Initially, we extracted features using the pretrained Yolo model, which was trained on the ImageNet dataset. The final few layers, which included two Dense and a Global Average Pooling layer, were swapped out with custom classification layers in order to modify the model for our classification purpose. Only the custom layers were adjusted during training; the basic model's weights were frozen to maintain the learnt characteristics.

3. Detection of Diabetic using nail infection

Customized the primary model for identification was CNN. TensorFlow is predominantly employed in this context. Then, abstractions and building blocks are provided by Keras for the creation of machine learning code. Due to its straightforward but comprehensive GUI, maplotlib was used to plot the results. The training and testing sets were divided into 80% and 20%, respectively. The layers that make up the data model's foundation are as follows 6 - Convolution2D layers with ReLU activation function, 6 – Max Pooling 2D layers, 1 - Flatten layer (to get output in the set of numbers) and 2 Dense layers, SoftMax activation function (to change the output into a probability). Due to the problem's size and abundance of data and parameters, the optimizer "Adam" was utilized. To acquire the best results, various Optimizers were tested with the model. In here mainly used two classes to identified diabetic nail or non-diabetic nail, using CNN model able to identify infection nail with good accurate. The parameters of batch size, learning rate, and epochs were hyperparameter tuned. A brute force approach was employed to determine the optimal epochs. To preprocess the data, it was shuffling, resizing, and rescaling. A 256 X 256 image was used since it matched the model parameter.

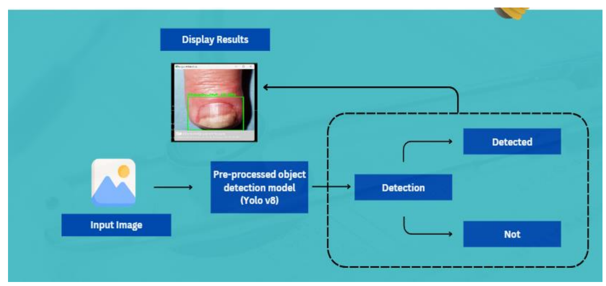


Figure 3 System diagram of predicting diabetics using nail infections

4. Detection of Diabetic Retinopathy (DR) and detection of diabetics

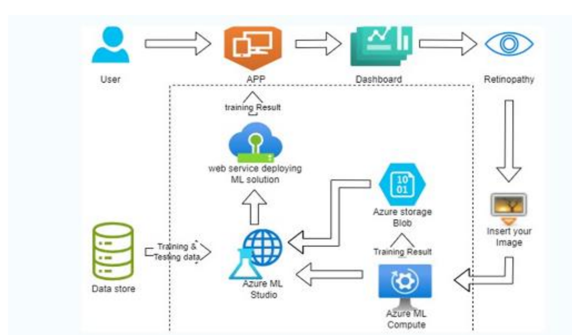


Figure 4 System diagram of diabetic retinopathy prediction

To distinguish between normal retina and diabetic retinopathy, a web application was created. The technological procedures included gathering data sets, choosing a model architecture, training the model, and integrating it with the web application. The proprietary CNN model using the ResNet50 architecture is used to identify infections. A bespoke convolutional neural network (CNN) with the ResNet50 architecture has been selected as the model architecture. It's possible that this architecture was created especially for the purpose of determining which diabetic retinopathy (DR) stages—No DR, Mild, Moderate, and Proliferative. For pre-processing the dataset TSNE visualization, images were changed to 224 x 224 pixels, and gaussian's blur were used. Convolutional layers with a ReLU activation function, pooling layers, MaxPooling2D layers, Dropout layers, and a Flatten layer make up the model architecture. By using convolutional filters, convolutional layers oversee collecting pertinent characteristics from the input images. The ReLU activation function is employed to add nonlinearity and improve the model's comprehension of intricate patterns. By reducing the spatial dimensions of the feature maps, pooling layers like MaxPooling2D help the model concentrate on the most crucial data. Dropout layers are used in training to reduce overfitting by arbitrarily turning off a portion of the neurons. Ultimately, the multidimensional feature maps are transformed into a 1D vector using a Flatten layer, and this vector is subsequently fed into dense layers for classification. The batch size of the data set was 32 and trained the model for 10 epochs and Adam optimizer was also applied.

Results and Discussion

A) Detecting Acanthosis Nigricans

The model was trained with 40 epochs and batch size was 32. The training accuracy was 94.37%. VG668 architecture was used because VG688 architecture is optimized for high-performance tasks.

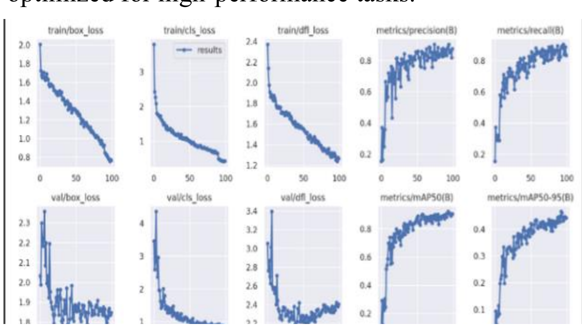


Figure 6 Train, Val and loss of acanthosis nigricans model

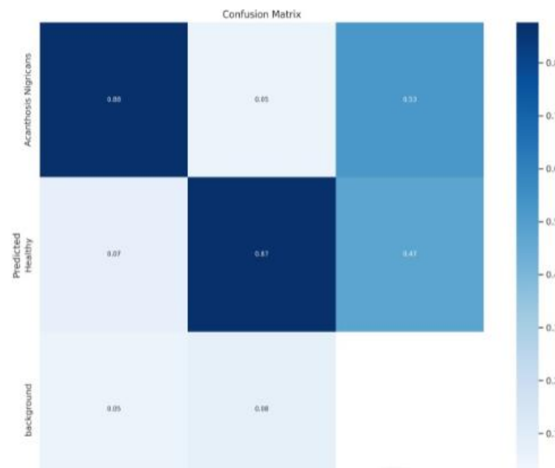
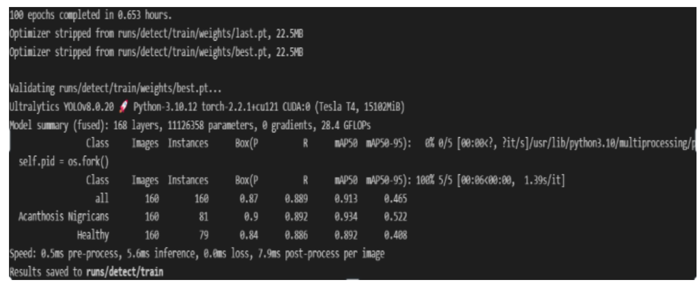


Figure 5 Confusion Matrix of Acanthosis nigricans



```
100 epochs completed in 0.653 hours.
Optimizer stripped from runs/detect/train/weights/last.pt, 22.5MB
Optimizer stripped from runs/detect/train/weights/best.pt, 22.5MB

Validating runs/detect/train/weights/best.pt...
Ultralytics YOLOv8.0.20 🚀 Python-3.10.12 torch-2.2.1+cu121 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 168 layers, 11126358 parameters, 0 gradients, 28.4 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95):   0% 0/5 [00:00<?, ?it/s]/usr/lib/python3.10/multiprocessing/p
  self.pid = os.fork()
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 5/5 [00:06<00:00,  1.39s/it]
                   all        160        160       0.87      0.889      0.913      0.465
  Acanthosis Nigricans        160         81        0.9      0.892      0.934      0.522
               Healthy        160         79       0.84      0.886      0.892      0.408
Speed: 0.5ms pre-process, 5.6ms inference, 0.0ms loss, 7.9ms post-process per image
Results saved to runs/detect/train
```

Figure 7 Epoch and accuracy of acanthosis nigricans model

B) Detecting Diabetic Foot Ulcers

The trained model's accuracy was 91.8%. This model predicted the test images perfectly. The dataset was divided in an 80:20 ratio into training and testing sets in order to train the model. With a batch size of 32, the training set was utilized to train the model for a period of 100 epochs. Categorical cross entropy was used as the loss function and the Adam optimizer was applied. The model performed consistently. The loss function used was categorical cross entropy, and the optimizer Adam was used. The accuracy of the model was used as the evaluation metric, and its performance was regularly tracked. The testing set was used to assess the model's performance following training. Test accuracy, or the percentage of correctly categorized wound images, and test loss, or the difference between expected and actual labels, were measured in this review.

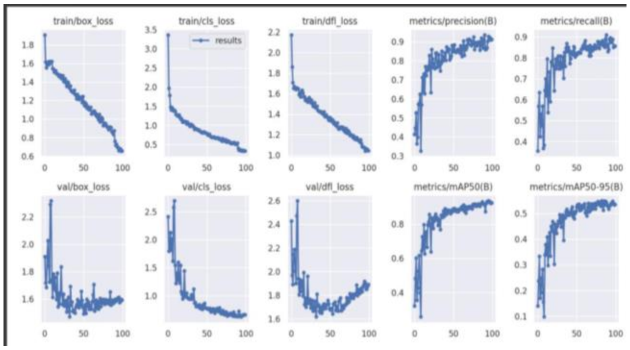


Figure 8 Train, val, and loss of foot ulcer model

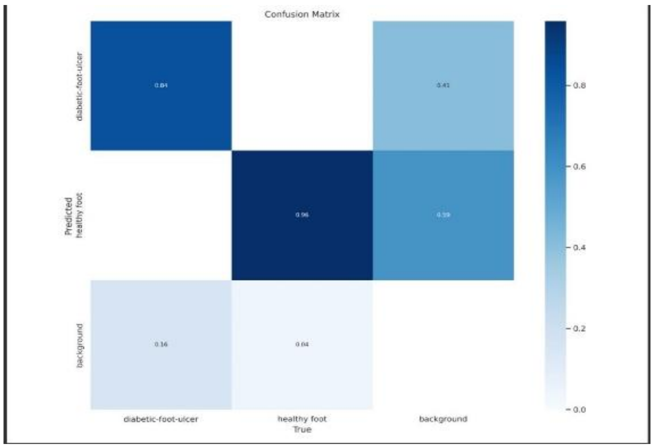


Figure 9 Confusion matrix of Foot ulcer model

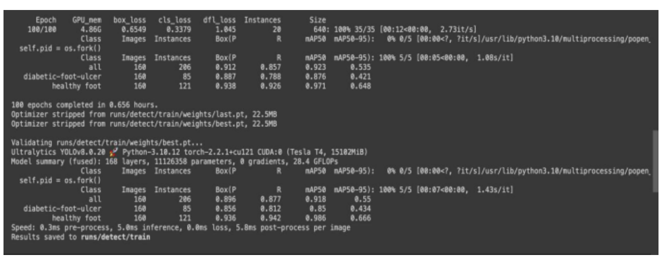


Figure 10 Epoch and accuracy of foot ulcer model

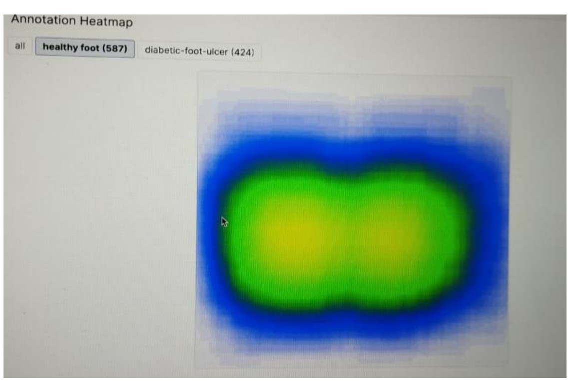


Figure 11 Heat map of healthy foot

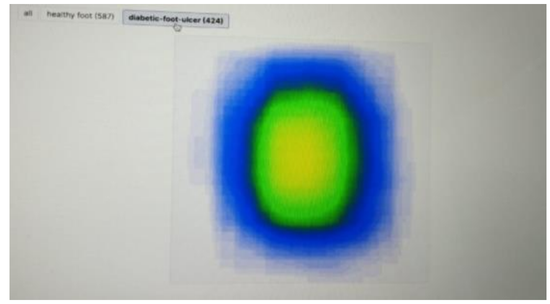


Figure 12 Heat map of diabetics' foot ulcer

C) Detecting Diabetic using nail infection

The accuracy of this model was 94.1%. A lower number was initially picked with a steady increase in value because research has shown that greater values for learning rate and batch size do not always produce higher results.

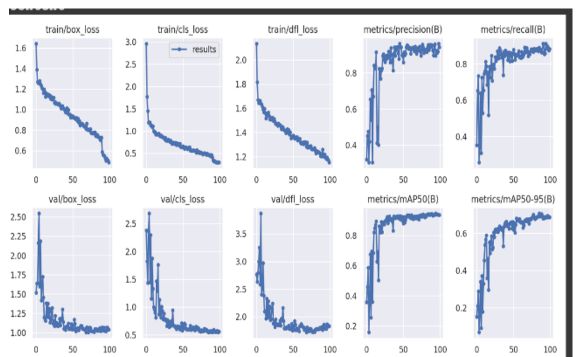


Figure 13 Train, val, and loss of nail infection model

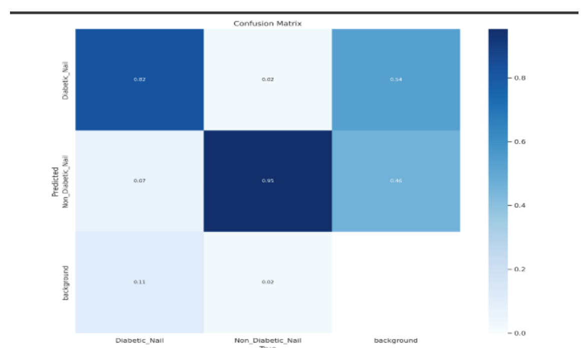


Figure 8 Confusion matrix of nail infection model

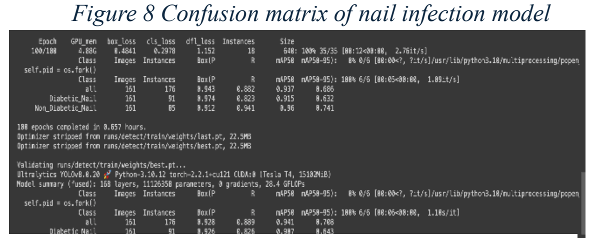


Figure 15 Epoch and accuracy of nail infection model

D) Detecting Diabetic Retinopathy

There is no negative impact from the accuracy fluctuating with a bigger number of epochs. The model's training accuracy was 98.78% with 10 epochs and a batch size of 32. ResNet50 architecture was used. Because ResNet50 is a deep convolutional neural network (CNN) with 50 layers, which allows it to learn complex features from images. The residual learning framework helps in training very deep networks by addressing the vanishing gradient problem. Precision in training and validation. The y-axis of the graph displays accuracy, and the x-axis displays the total number of epochs.

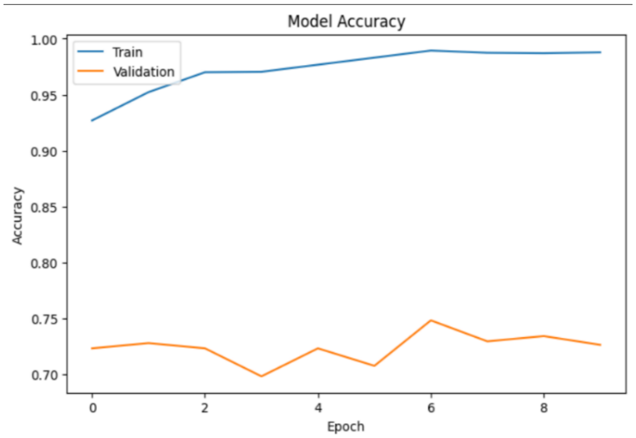


Figure 16 Model Accuracy graph of diabetic retinopathy

```
Epoch 1/10
80/80 [==============================] - 749s 9s/step - loss: 0.2239 - accuracy: 0.9269 - val_loss: 1.5053 - val_accuracy: 0.7234
Epoch 2/10
80/80 [==============================] - 747s 9s/step - loss: 0.1514 - accuracy: 0.9522 - val_loss: 1.6208 - val_accuracy: 0.7281
Epoch 3/10
80/80 [==============================] - 758s 9s/step - loss: 0.1176 - accuracy: 0.9700 - val_loss: 1.8930 - val_accuracy: 0.7234
Epoch 4/10
80/80 [==============================] - 759s 9s/step - loss: 0.1185 - accuracy: 0.9704 - val_loss: 1.8986 - val_accuracy: 0.6984
Epoch 5/10
80/80 [==============================] - 762s 10s/step - loss: 0.0977 - accuracy: 0.9767 - val_loss: 1.5369 - val_accuracy: 0.7234
Epoch 6/10
80/80 [==============================] - 759s 9s/step - loss: 0.0734 - accuracy: 0.9830 - val_loss: 1.9256 - val_accuracy: 0.7078
Epoch 7/10
80/80 [==============================] - 763s 10s/step - loss: 0.0550 - accuracy: 0.9893 - val_loss: 2.2453 - val_accuracy: 0.7484
Epoch 8/10
80/80 [==============================] - 762s 10s/step - loss: 0.0589 - accuracy: 0.9874 - val_loss: 1.9371 - val_accuracy: 0.7297
Epoch 9/10
80/80 [==============================] - 759s 9s/step - loss: 0.0500 - accuracy: 0.9870 - val_loss: 1.5653 - val_accuracy: 0.7344
Epoch 10/10
80/80 [==============================] - 767s 10s/step - loss: 0.0438 - accuracy: 0.9878 - val_loss: 1.8338 - val_accuracy: 0.7266
```

Figure 17 Epochs and Accuracy

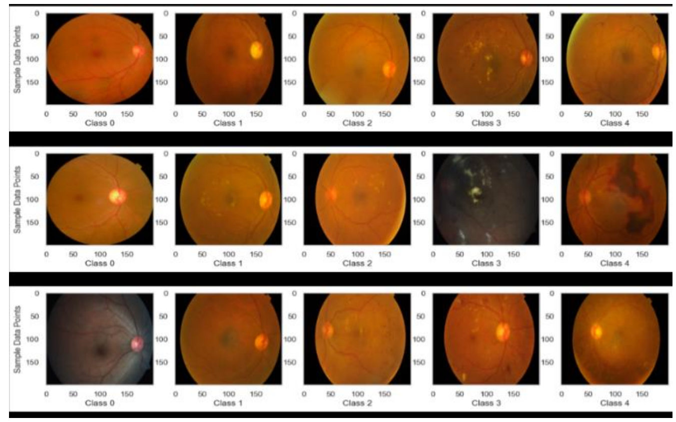


Figure 18 Re-sized into 224 X 224

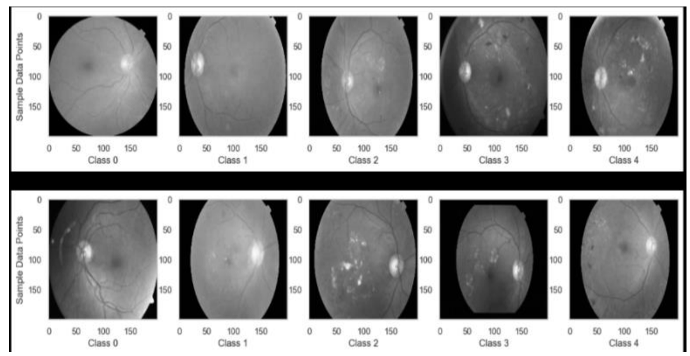


Figure 19 Grey-scale images

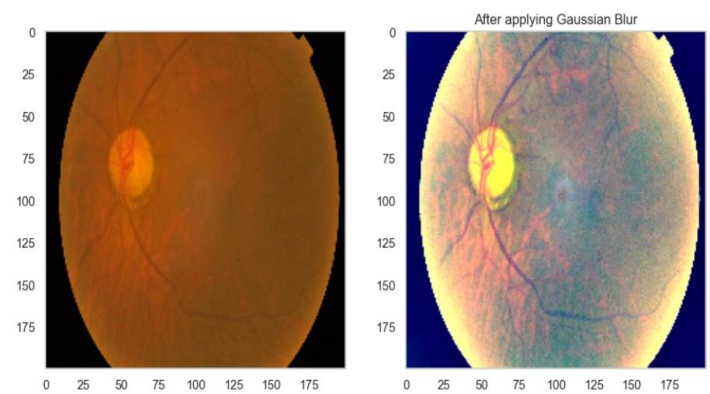


Figure 20 Apply Gaussian's Blur

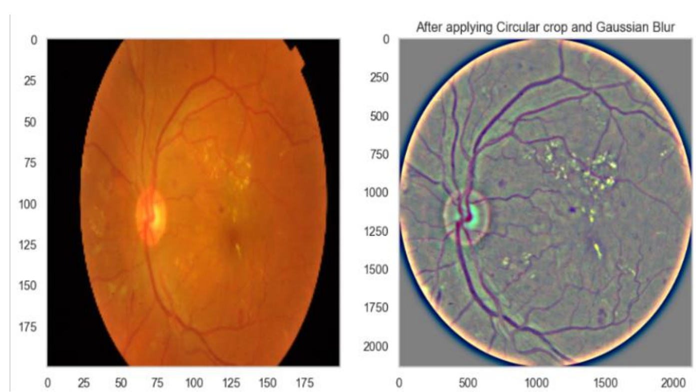


Figure 21 After applying Gaussian's Blur and circular crop

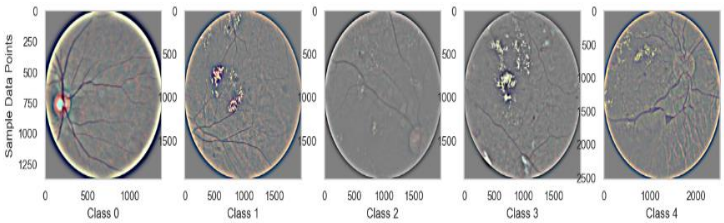


Figure 22 Overview of pre-processed images with Gaussian's Blur

The reason behind using Gaussian blur is because it is a very effective way to smooth out images and reduce noise. By averaging the values of the pixels in a neighborhood around each pixel, Gaussian blur can help to reduce the effects of random noise and other artifacts in the image. This can be useful in a variety of applications, such as image recognition, computer vision, and machine learning. We can vividly see retinal blood vessel and macula damage after applying gaussian blur.

Conclusion

The purpose of this research is to predict diabetics using unconventional indicators. Therefore, four major symptoms are used in here to predict diabetics using machine learning. Such as, acanthosis nigricans, foot ulcers, nail infection and diabetic retinopathy. Four CNN models were used for this study in an effort to identify the most appropriate predictions. Taking into account the outputs produced by the four models utilized in image categorization, each model determine the severity level, some more study has been conducted. Data pre-processing techniques were applied, and a custom Python operation was refined to provide the severity level, in order to map actual affected areas. To improve the precision of object detection model VG688 architecture, Yolov5 architecture and ResNet50 architecture were used in order to improve the accuracy. they are also wiling to expand the early detection feature of diabetic prediction in the future.

References

1. Kart, Ö., Mevsim V.,Kut A., Yürek İ., Altın AÖ., Yılmaz O., (2017) „A mobile and web-based clinical decision support and monitoring system for diabetes mellitus patients in primary care: A study protocol for a randomized controlled trial‟, BMC Medical Informatics and Decision Making, 17(1). doi:10.1186/s12911-017-0558-6.

2. M. M. Phiske, "An approach to acanthosis nigricans," Indian Dermatology Online Journal, vol. 5, no. 3, pp. 239–249, 2014, doi: https://doi.org/10.4103/2229-5178.137765.

3. Y. Zhai and W. Yu, "A Mobile App for Diabetes Management: Impact on Self-Efficacy Among Patients with Type 2 Diabetes at a Community Hospital," Medical Science Monitor, vol. 26, Sep. 2020, doi: https://doi.org/10.12659/msm.926719.

4. Fraiwan, L., AlKhodari, M., Ninan, J. et al. Diabetic foot ulcer mobile detection system using smart phone thermal camera: a feasibility study. BioMed Eng OnLine 16, 117 (2017). https://doi.org/10.1186/s12938017-0408-x.

5. D. M. Anisuzzaman, Y. Patel, B. Rostami, J. Niezgoda, S. Gopalakrishnan, and Z. Yu, "Multi-modal wound classification using wound image and location by deep neural network," Scientific Reports, vol. 12, no. 1, Nov. 2022, doi: https://doi.org/10.1038/s41598-02221813-0.

6. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Jun. 2018, doi: https://doi.org/10.1109/cvpr.2018.00474.

7. L. Alzubaidi et al., "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," Journal of Big Data, vol. 8, no. 1, Mar. 2021, doi: https://doi.org/10.1186/s40537021-00444-8.

8. Schröder and M. Schulz, "Monitoring machine learning models: A categorization of challenges and methods," Data Science and

Management, Aug. 2022, doi: https://doi.org/10.1016/j.dsm.2022.07.004.

9. I.Kurniastuti and Ary Andini, “Determination of RGB in Fingernail Image as Early Detection of Diabetes Mellitus,” Oct. 2019, doi: https://doi.org/10.1109/icomitee.2019.8920876.

10. R. Ghosh, K. Ghosh and S. Maitra, "Automatic detection and classification of diabetic retinopathy stages using CNN," 2017 4th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2017, pp. 550-554, doi: 10.1109/SPIN.2017.8050011.