Classifying Diabetic Foot Ulcers Using Deep Learning Techniques

Harshitha Poolakanda Somanna
Student ID: *x22150366*
Email ID: x22150366@student.ncirl.ie
MSC in Data Analytics
National College of Ireland

Jose Geo Vattolly
Student ID: *x22139508*
Email ID: x22139508@student.ncirl.ie
MSC in Data Analytics
National College of Ireland

***Abstract*—. Diabetic Foot Ulcer(DFU) is a recurrent side effect in diabetes patients and early detection could help in severe complications. Automatic analysis of DFU using deep learning techniques are gaining popularity in health care as they aid radiologists in accurately classifying the disease based on the foot images. In our study, a hybrid of Multi-Layer Perceptron (MLP) and Convolutional neural network (CNN) techniques is coupled with Gray-Level Co-occurrence Matrix (GLCM) is implemented to classify the diabetic foot ulcer images from a normal healthy foot. Evaluation and validation has been done to check the performance of our model and the results show a satisfactory performance to differentiate the diabetic foot ulcers from a healthy one with AUC score of 69%.**

Keywords— Diabetic Foot Ulcer, CNN, MLP, GLCM .

I. INTRODUCTION

Diabetes Mellitus(DM) has several implications and Diabetes Foot Ulcers(DFU) is one of the major complications of diabetes and it is reported that upto one-third of patients with diabetes might suffer with DFU and its occurrence is more in men with type 2 diabetes. Foot ulcers damage the underlying skin and exposes the layer within causing damage to the feet and bone. A person with DFU may fail to recognize the disease in their early stages and is more prone to lower limb amputation as the risk of healing the wound is poor in such patients. Also, the patients with DFU are in risk of development of peripheral neuropathy and peripheral vascular disease[1]. It is critical to identify patients who are at the risk of ulceration, any early signs of skin breakdown in the foot to commence appropriate therapy and avoid the progression of development of foot ulcers. However, regardless of the severity of this condition, early detection of foot ulcers in diabetes patients allows for timely intervention and can prevent the progression to severe stages.

Manual methods of visualization of photographs of ulcers for initial evaluation and subsequent reviews to check the progress of ulcer progression by the clinicians is time consuming and may be prone to human error and hence accurate detection and classification of ulcers in foot into diabetic foot ulcers and other type of foot ulcers plays a crucial role in medical field. Deep learning techniques are gaining popularity in medical domain as computer aided diagnosis(CAD) in medical image analysis has bought a revolutionary change in health care. In contrast to the traditional machine learning approaches which require feature extraction along with domain experience, deep learning techniques can automatically extract features shifting from manual feature design to a more data centric approach [2]. Many research has been carried out in the classification of diabetic foot ulcers and for medical use, accuracy of classification is not sufficient but it needs to be improved by modifying the models, adding layers in the dense output layers, fine tuning the model are all necessary steps towards improvement[3].

A wealth of data is found in medical images and researchers are actively working towards automatic classification and identifying medical conditions using machine learning, deep learning and transfer learning techniques. Deep learning techniques have demonstrated remarkable performance and their adoption in health care has witnessed a substantial surge. Convolutional Neural Network(CNN) have gained immense popularity among deep learning approaches as their adaptability extends to various applications like image classification, object detection, facial recognition and medical image analysis[4]. The unique feature of CNN is to automatically learn hierarchical patterns and features from raw pixel data through a series of specialized layers and activation functions. However, before implementing CNN, suitable pre-processing must be ensured to prevent under fitting for lesser volume of data.

In our analysis, we have used the publically available dataset from kaggle with a total of 1217 images. CNN and Multi - layer perceptron (MLP) based classification techniques are applied on the DFU dataset where 513 images are of diabetic foot ulcers, 543 images are of healthy skin(shown in Fig 1.) and 167 images are a mixed of DFU images and healthy skin used for testing and validating our results.

Fig 1. Abnormal and Normal Foot images from DFU dataset

Considering the analysis of presented above, we have formulated our research question as *"How much can the combination of MLP and CNN algorithms improve the classification of images in Diabetic Foot Ulcer?"*

The following sections will look into an extensive examination of the conducted research. In section two, we will look into indepth research in the related field, with their constraints and key findings. Section three has details on the methodology with distinct subsections and section four will discuss on the results and evaluation followed by conclusion and future work in the last section.

II. Literature Review

Numerous research and analysis has been critically reviewed inorder to make an informed decision on the methodology for the classification of foot ulcers into Diabetic Foot Ulcers(DFU) and normal healthy foot.

In this study [5], the proposed approach was to enhance the accuracy of DFU using plantar thermos-grams captured from both diabetic and non diabetic patients. The dataset consists of 122 images and were classified into healthy foot and DFU and compared against three CNN frameworks, VGGNet, MatConvNet and DenseNet. A modified version of DenseNet – 201 was used which consists of initial convolutional and max-pooling layers, followed by Dense Conv blocks and transition layers. The proposed approach evaluated the performance using performance metrics like accuracy, sensitivity, specificity, precision, and F1-Score and it showed that it showed improved accuracy among the existing CNN architectures. A similar study[6] used CNN models like Inception V3, VGG16 and VGG19 to classify 100 non ulcer and 119 ulcer foot images for input layer of 224x224x3. All the model were trained and convolution layers were employed with ReLu and Max-Pooling. Classifiers like SVM, KNN, Logistic regression and AdaBoost was used for classification among which Inception-V3-based SVM approach outperformed other methods with 99.8% accuracy. However, the dataset was not extensive enough to improve the generalizability of the proposed model.

The effectiveness of MLP and CNN in classifying handwritten images was studied in this research[7]. MNIST database is used to optimize the MLP model where MLP's performance was enhanced by adjusting various factors like activation functions, dropout layers, neurons, and hidden layers. Superior accuracy of about 97.49%, 97.98%, and 98.24% was achieved with training set of 30,000, 40,000, and 60,000 images respectively. While MLP showcases superior accuracy, it requires more time for training and predictions compared to CNN, suggesting potential avenues for optimizing and streamlining its performance.

A deep CNN method was used to accurately identify ulcers in images taken through Wireless Capsule Endoscopy (WCE) with dataset ranging from 1000 to 10000 WCE images where data augmentation was applied to increase the dataset[8]. CNN structure, with four convolutional layers and filters were applied and parameters like epochs, pooling strategies, learning rate, layer count, optimizer, activation functions, and dropout technique were fine-tuned. This proposed method showed impressive performance, with high accuracy, precision, recall, F1-score, sensitivity, specificity, and ROC-AUC values, proving its proficiency in ulcer detection within WCE images. For accurate identification of unhealthy silkworms and stop spreading of diseases to other cocoons, a total of 550 images were classified[9]. GLCM was used for feature extraction and RF and Light GBM were used as classifiers and CNN was used with auto generated features. The CNN model was the most effective, with an accuracy of 85%. Mapping burned areas efficiently is crucial, particularly in forest and land fire-prone regions. This study[10] assesses different models that utilize optical data, synthetic aperture radar (SAR) data, and a combination of both to identify burned areas using Sentinel-1 and Sentinel-2 data where GLCM was used for feature extraction. MLP and CNN was implemented using TensorFlow and Keras libraries while RF was implemented. CNN outperformed MLP and RF and proved with an accuracy of 99.86% that combining optical and SAR data, especially using CNN, is the most dependable method for accurate mapping of burned areas inspite of the challenges over cloud cover .

The need to manage the transmission and storage of 4K content efficiently has resulted in compression or downsizing. Traditional methods for assessing image quality aren't suitable due to the unique distortions introduced by up scaling and the high spatial resolution. To address this, a BIQA model[11] using deep learning specifically for 4K content is proposed where the model selects key patches from 4K images using GLCM and is enhanced for computational efficiency and quality prediction. CNN is used to extract visual features from intermediate layers and two MLP is used to map these features class probabilities and quality scores for each patch, leading to an encompassing overall quality index. The proposed 4K BIQA model effectively evaluates visual quality and distinguishes real from pseudo 4K content.

In this study[12], the DFU2021 dataset with 15,683 DFU images were used to classify infection only, ischaemia only, both infection and ischaemia and normal skin. DenseNet121 and EfficientNetB0 were applied in which DenseNet121 resulted with macro-average F1-Score of 0.55 and AUC of 0.88. EfficientNetB0 works best with ImageNet pretrained model and data augmentation and for binary classification, it achieved high accuracy in F1-Score for ischaemia recognition (0.83) and good result in infection recognition (0.69). However, the classification of both the conditions is a costly procedure and time consuming.

To detect the flaw in welded components, GLCM and ANN was proposed in this study[13] where a total of 79 radiographics images were classified in which 8 were defective with 88.06% accuracy. GLCM was used to extract second order features and ANN for classification. This method helped to improve noise removal and contrast enhancement. This study[14] employed GLCM-CNN Model with ABL Strategy to distinguish malignant and benign polyps for a small dataset of 63 sample images. Two fold cross validation was used for evaluation and the AUC had results ranging from 0.5% to 3.7%, reaching 91.13% AUC for polyp classification. For ischemia and infection classification in DFU patients, DFU2020 dataset has been employed for transfer learning and classification[15]. Different pre-trained models like AlexNet, VGG16/19, GoogLeNet, ResNet 50/101, MobileNet, SqueezeNet, and DenseNet were used where ResNet achieved higher performance among different models. This research[16] proposes a classification of breast USG images by using some texture features into two classes on 57 USG images which grouped into 27 anechoic cases and 30 hypoechoic cases. Texture analysis involves GLCM and FBM method and MLP is used for classification where K-fold cross-validation used for evaluating training process. The proposed model achieved 91.23% accuracy, 95.83% sensitivity, and 87.88% specificity. The author in this study[17] used Fashion-MNIST dataset consisting of 60,000 28x28 pixel grayscale images of clothing items which are assigned to a label from 10 different classes. CNN and MLP were used and optimized using hyperparameters. The images in the input layer were flattened to 1D and ReLU activation function was used. The model was trained using Stochastic descent and the results were compared with and without hyperparameters where CNN with hyperparameters yielded 91.5% accuracy.

After extensive analysis of related work, we can see that CNN and MLP techniques are widely used in medical image analysis and classification. Also GLCM has been employed in most of the study, be it in medicine, fashion and art for feature extraction. Therefore, the findings have provided valuable perspectives and sources of inspiration for crafting the methodology and assessment approach for classification models utilizing deep learning methodologies.

III. Methodology

We have used KDD methodology to classify the DFU images into abnormal and healthy and the process diagram is as shown in Fig 2. The method involves a) data pre-processing where the data is split into train set, test set and validation set and also the image is resized into 256 x 256, b) feature selection and feature extraction using GLCM, c) model building using CNN and MLP and d) evaluation of the results.

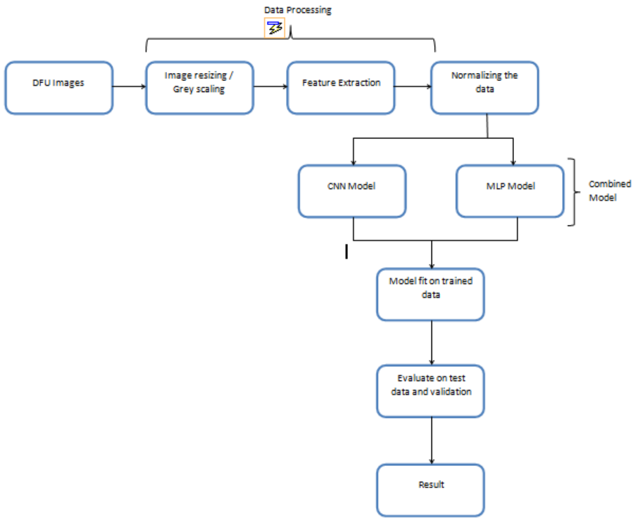

Fig 2. KDD methodology for DFU Image Classification

A. *Data Pre-Processing*

1. **Data Splitting:** The original dataset was split using the splitfolders is used to split the images in the input_folder into training, validation, and testing subsets in the ratio 80:10:10. Before splitting the images into different folders, the image files are shuffled based on a seed value, which was 1055 here.

2. **Image Pre-Processing:** here the preprocessing Image takes the image as an input and the BGR image format is converted to RGB format using OpenCV. Then the image is resized to a fixed size of 256x256 pixels and then converted to grayscale. The images are converted from 3D RGB color space to 1D grey scale images(Fig 3). These pre-processing tasks help to standardize the input images and extract relevant features for the model to perform classification.

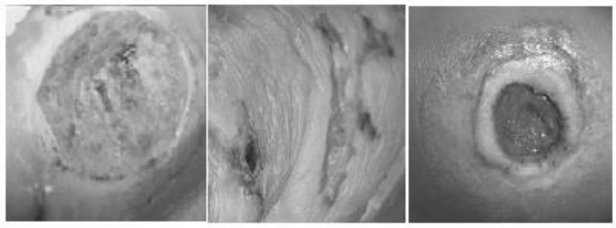

Fig 3. GreyScale DFU images of Abnormal Skin

3. **Feature extraction using GLCM:** In feature extraction, the raw pixel data is converted into a set of relevant and informative features that can be used for various tasks such as image classification, object detection and recognition and GLCM is widely used for feature extraction. Texture analysis plays a significant role in medical image processing, especially when distinguishing between objects in an image relies more on their texture qualities rather than just their intensity or other features. The variance in texture can be understood by observing variance in each pixel[18].

   Here, GLCM is applied to extract relevant features from the images. For each image, the GLCM properties like Energy, Correlation, Homogeneity, Dissimilarity and Contrast, were computed at different distances and angles[19]. We were able to extract 25 features as shown in Fig 4.

	Energy0	Corr0	Diss_sim0	Homogen0	Contrast0	Energy1	Corr1	Diss_sim1	Homogen1	Contrast1
0	0.060986	0.911398	2.407552	0.357245	11.015824	0.047057	0.748333	4.179996	0.227793	31.263556
0	0.062215	0.975192	1.986045	0.414050	7.950077	0.043568	0.884575	4.316344	0.234500	36.325423
0	0.041603	0.954580	3.096936	0.316277	19.947518	0.030343	0.851154	5.827523	0.183230	65.132550
0	0.049331	0.946233	2.562975	0.355541	12.785095	0.040450	0.892653	3.765872	0.250292	25.394979
0	0.073040	0.993503	1.085524	0.623829	3.483042	0.055420	0.974453	2.259187	0.440866	13.712281
...	...	...	...	...	...	...	...	...	...	...
0	0.044156	0.993587	2.282675	0.425146	13.572932	0.029020	0.962095	5.641613	0.228165	79.251606
0	0.025987	0.959310	5.405178	0.210136	59.406281	0.018714	0.836610	11.160897	0.104753	236.628597
0	0.032805	0.992293	2.547564	0.372829	14.165365	0.022302	0.959488	5.987648	0.198418	74.028749
0	0.022393	0.981866	4.455990	0.261127	53.425352	0.016556	0.950920	8.125834	0.147127	144.335783
0	0.063750	0.990867	4.895297	0.365955	70.831633	0.055738	0.955151	11.107769	0.237982	347.641150

843 rows × 25 columns

Fig 4. Extracted features from train set

4. **Data Normalization:** Normalization of data is an important step in all machine learning tasks, as well as in image classification. Here, we scale the input data to a standard range and improve the convergence of optimization algorithms and also enhance the performance of machine learning models[20].

Here, the normalization ensures that pixel values are in a consistent and bounded range, which is typically between 0 and 1. To normalize our data, the arrays are converted to float and the pixel values are divided by 255 which ensures that pixel values are scaled to the range of [0, 1]. By doing this, we can ensure that each pixel value in the image is represented as a decimal value between 0 and 1. Also, the greyscaling is a type of normalization which reduces the illumination' s differences in the images. Overall, normalization helps to learning rate of the neurons in the network to improve.

IV. Model Implementation

A. CNN Architecture

Convolution Neural network and Multi-Layer Perceptron are integral components of deep learning techniques used in image classification, feature extraction and optimization.

Convolutional layers, pooling layers, and fully connected layers are the three layers in CNN(fig 5) with two important parameters to consider, the drop out layer and the activation function[21]. In convolutional layers, the network detects important features from input pictures. It uses matrix multiplication to create a new picture that goes to the next layer. Activation functions like sigmoid, tanh, or ReLU are used to improve accuracy. Pooling layers make the picture smaller and prevent the network from focusing on small details. Different types of pooling include max, average, and min pooling. The final FC layer takes a squashed line from the last pooling layer and determines what the picture is showing. Probabilities for each choice are given by the softmax function if there are many options.

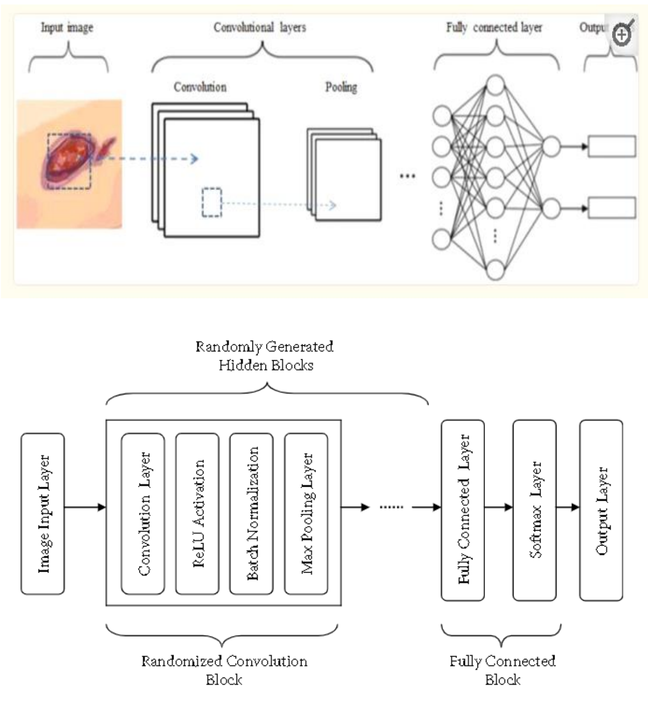

Fig 5. CNN Architecture for image classification

B. MLP Architecture

Multi-Layer Perceptron is a deep-learning technique that contains multiple layers(fig 6) with nodes that is interconnected. The MLP network is like a building with different levels: a starting point, hidden floors, and an endpoint[22]. These levels sort out its work. It learns by careful tweaking, using a method that involves adjusting things step by step. This helps the network understand things better, sort of like how we learn from our mistakes. The inner layers of the network have cells that do specific tasks. Imagine these cells as helpers in different rooms. They use different rules to figure things out. Some rooms use one rule, others use another. The network most commonly learns by examining its mistakes and getting better. It's like when we make a wrong guess and then try to fix it. The process of improving is a bit like finding your way in a dark room with a flashlight. If the light is too small, it takes a while to see where you're going. But if it's too big, you might miss important details. So, picking the right size of light is crucial. The goal of learning is to minimize errors. When learning happens step by step, it's usually about fixing one mistake at a time. But when we want to see how well the network is doing overall, we need to look at all the mistakes together. It's kind of like checking how well we've improved not just on one thing, but on everything we're trying to learn.

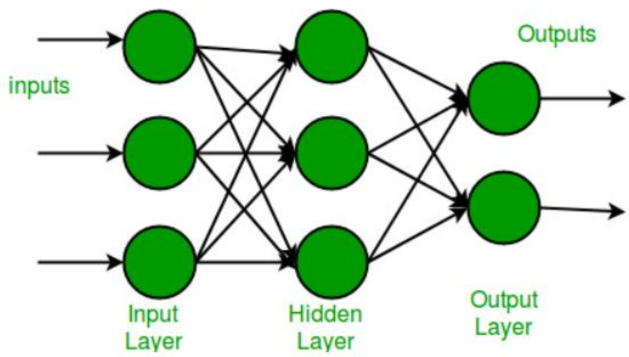

Fig 6. MPN Architecture for image classification

To detect Diabetic Foot Ulcer(DFU), CNN architecture has been used here. It used three convolutional neural layers in that each had an individual pooling layer and filters of size 16, 32, and 32 which helps to identify the patterns from the images. The kernel size was kept as (3,3) and the activation function used in this model was Rectified linear unit (RelU) which helps in identifying the non-linearity in the network. The pooling layer was set to (5,5) with a stride of 2 which aids in decreasing the dimension of the image and captures the main features of the image. These all layers will be flattened to form a single vector and forwarded to the fully connected dense layer. Table 1 shows the parameters used in CNN models.

The MLP with total of two layers has been used here. It makes a prediction and delivers the output in the appropriate class in the output layer. The activation function used in this model is SoftMax which is used to transform the output value into probability distribution to connect the right class. In this project, MLP is mainly used to extract the features with the help of GLCM. The implementation is done by combining CNN and MLP helped in increasing the feature extract potential of the model. ADAM optimizer was used in this study with a learning rate of 0.5. The model summary is shown in fig 7 and model plot in fig 8.

Parameters	Optimal value
Convolutional layer 1	16
Convolutional layer 2	32
Convolutional layer 3	32
Strides	2
Kernal size	(3,3)
Pooling layer size	(5,5)
Activation function	ReLU and SoftMax
Optimizer	ADAM
Learning Rate	0.05

Table 1. Parameters used in CNN model

```
Model: "sequential_20"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 Dense1 (Dense)              (None, 8)                 208

 Dense2 (Dense)              (None, 4)                 36

=================================================================
Total params: 244
Trainable params: 244
Non-trainable params: 0
_________________________________________________________________
None
Model: "sequential_21"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 Conv1 (Conv2D)              (None, 64, 64, 16)        160

 max_pooling2d_30 (MaxPoolin  (None, 30, 30, 16)       0
 g2D)

 Conv2 (Conv2D)              (None, 28, 28, 32)        4640

 max_pooling2d_31 (MaxPoolin  (None, 12, 12, 32)       0
 g2D)

 Conv3 (Conv2D)              (None, 10, 10, 64)        18496

 max_pooling2d_32 (MaxPoolin  (None, 3, 3, 64)         0
 g2D)

 flatten_10 (Flatten)        (None, 576)               0

 Dense (Dense)               (None, 64)                36928

=================================================================
Total params: 60,224
Trainable params: 60,224
Non-trainable params: 0
_________________________________________________________________
```

Fig 7. Model Summary of CNN and MLP

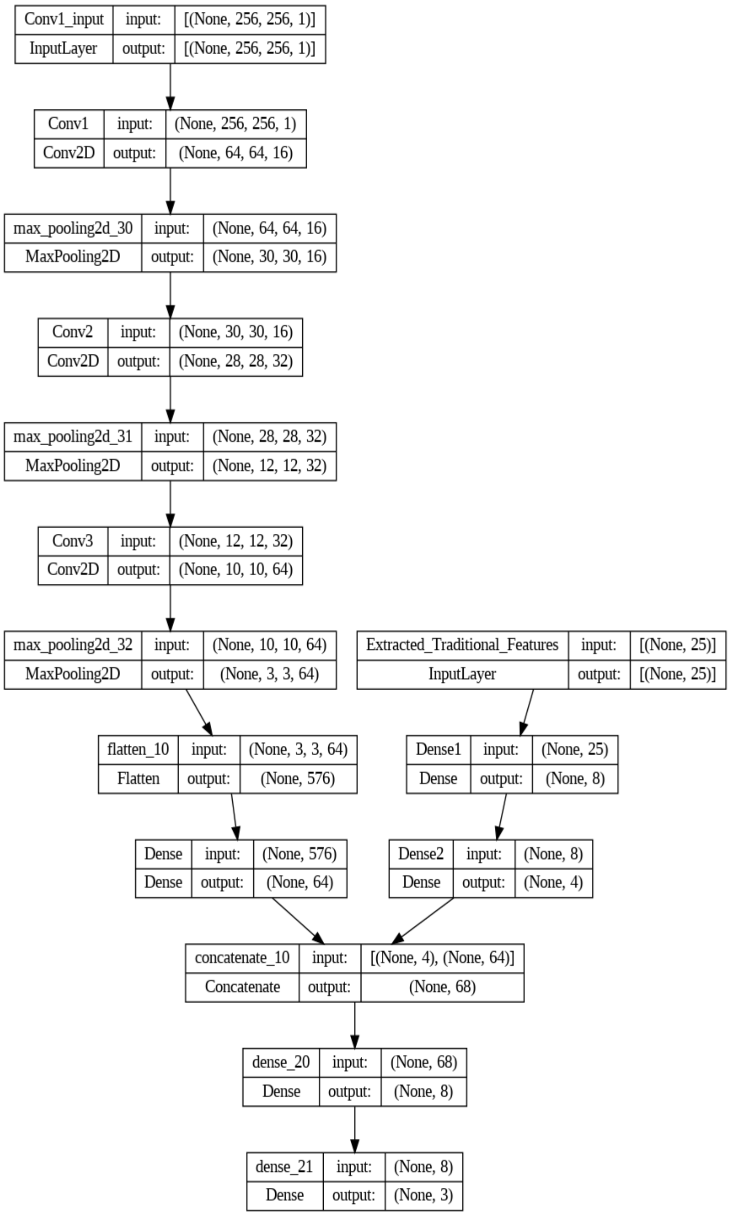

Fig 8. Model Plot

V. Results and Model Evaluation

In this section, we evaluate the model results to assess the effectiveness of our trained data. Adam optimizer with a learning rate of 0.05 is used which adjusts the weights to minimize the loss function. AUC is a evaluation metric used in machine learning and classification tasks, especially for binary and multi-class classification. The overall performance of a classification model is quantified by its ability to differentiate positive and negative examples. With AUC, we can minimize Type 1 and Type 2 errors in medical field. From fig 9, we can see that the training and validation loss has a decreasing trend to a point of stability. It indicates that the model is best fit. However, continuing further leads to overfitting which is not desirable. Fig 10 depicts the model's accuracy indicating a improved performance.

The CNN model and MLP model combined resulted in AUC score of 0.69, thereby indicating that the model can distinguish the abnormal/ulcer foot images from normal skin/healthy skin. Overall, the combined model of CNN and MLP demonstrated a good performance in classifying the

Diabetic Foot Ulcers from the healthy foot ulcers with the least amount of loss.

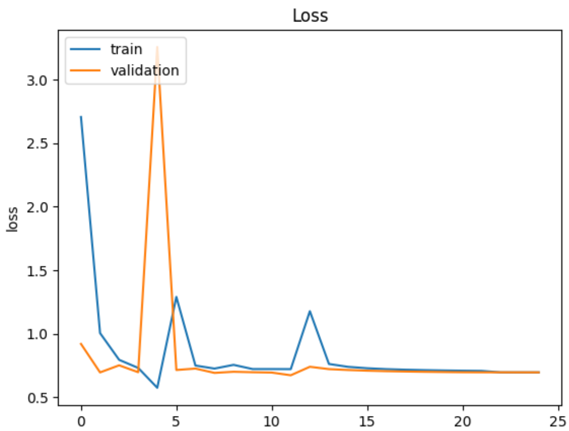

Fig 9. Training vs Validation loss

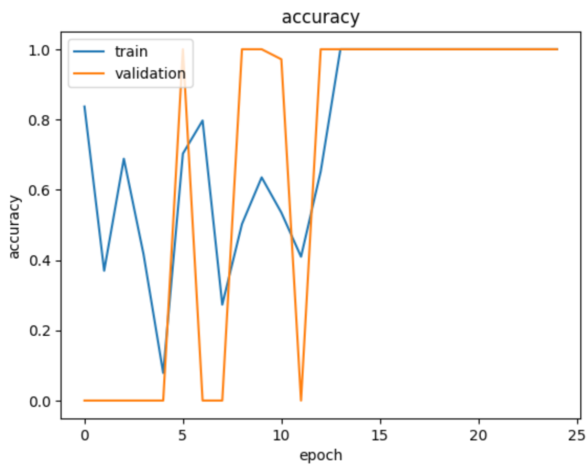

Fig 10. Model accuracy with epoch vs accuracy

VI. CONCLUSION AND FUTURE WORK

Diabetic foot ulcers have severe complications and take lot of time to heal. If unchecked and left untreated, ulcers develop on the foot which spreads to the limb which leads to limb amputation. Deep learning techniques are gaining popularity in detecting ulcers and classifying them based on the images. In our research, for better DFU classification, we focused on classifying diabetic foot ulcers from normal healthy foot. To do so, we employed combination of Convolutional Neural Networks, Multi Layer Perceptron and GLCM for our feature extraction on the publicly available DFU dataset. This research signifies the effective implementation of deep learning techniques and the evaluation metric of AUC showed an accuracy of 69%. The model can be further improved using a larger dataset with wide range of categories.

As a future work, the model will be tested against a large number of images to check for its robustness. Also, the dataset could include variety of foot ulcers and can be differentiated into categories of foot ulcers. Transfer learning techniques is a popular technique in image classification and these techniques can be employed to compare the model’s performance.

REFERENCES

[1] R. Reardon, D. Simring, B. Kim, J. Mortensen, D. Williams, and A. Leslie, "The diabetic foot ulcer," Australian Journal of General Practice, vol. 49, no. 5, pp. 250-255, 2020.

[2] S. Min, B. Lee, and S. Yoon, "Deep learning in bioinformatics," Briefings in Bioinformatics, vol. 18, no. 5, pp. 851-869, 2017.

[3] S. S. Nakka, B. Chakraborty, T. Sanada, W. Wang and G. Chakraborty, "Identification and Classification of Diabetic Foot Ulcers by Deep Neural Networks: A Comparative Study," *2022 IEEE 5th International Conference on Knowledge Innovation and Invention (ICKII)*, Hualien, Taiwan, 2022, pp. 14-17, doi: 10.1109/ICKII55100.2022.9983553.

[4] M. Kim, J. Yun, Y. Cho, K. Shin, R. Jang, H. J. Bae, and N. Kim, “Deep learning in medical imaging,” Neurospine, vol. 16, p. 657, 12 2019. [Online]. Available: /pmc/articles/PMC6945006/ /pmc/articles/PMC6945006/?report=abstract

[5] M. S. Prabhu and S. Verma, "A Deep Learning framework and its Implementation for Diabetic Foot Ulcer Classification," 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2021, pp. 1-5, doi: 10.1109/ICRITO51393.2021.9596380.

[6] S. Mohanty, S. Goel, R. Nijhawan and S. Gupta, "Identification of Diabetic Foot Ulcer in Images using Machine Learning," 2021 19th OITS International Conference on Information Technology (OCIT), Bhubaneswar, India, 2021, pp. 221-225, doi: 10.1109/OCIT53463.2021.00052.

[7] C. Xu, "Applying MLP and CNN on Handwriting Images for Image Classification Task," 2022 5th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), Wuhan, China, 2022, pp. 830-835, doi: 10.1109/AEMCSE55572.2022.00167.

[8] V. Vani and K. M. Prashanth, "Ulcer detection in Wireless Capsule Endoscopy images using deep CNN," Journal of King Saud University-Computer and Information Sciences, vol. 34, no. 6, pp. 3319-3331, 2022.

[9] P. S. Shilpashree, A. G. Karegowda, K. V. Suresh and L. R. A, "Classification of Healthy and Diseased Silkworms using Ensemble Learning and CNN," 2023 International Conference on Smart Systems for applications in Electrical Sciences (ICSSES), Tumakuru, India, 2023, pp. 1-5, doi: 10.1109/ICSSES58299.2023.10200374.

[10] A. I. Lestari, M. Rizkinia and D. Sudiana, "Evaluation of Combining Optical and SAR Imagery for Burned Area Mapping using Machine Learning," 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), NV, USA, 2021, pp. 0052-0059, doi: 10.1109/CCWC51732.2021.9376117.

[11] W. Lu et al., "Deep Neural Network for Blind Visual Quality Assessment of 4K Content," in IEEE Transactions on Broadcasting, vol. 69, no. 2, pp. 406-421, June 2023, doi: 10.1109/TBC.2022.3221689.

[12] M. H. Yap, B. Cassidy, J. M. Pappachan, C. O’Shea, D. Gillespie and N. D. Reeves, "Analysis Towards Classification of Infection and Ischaemia of Diabetic Foot Ulcers," 2021 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI), Athens, Greece, 2021, pp. 1-4, doi: 10.1109/BHI50953.2021.9508563.

[13] J. Kumar, S. P. Srivastava, R. S. Anand, P. Arvind, S. Bhardwaj and A. Thakur, "GLCM and ANN based Approach for Classification of Radiographics Weld Images," 2018 IEEE 13th International Conference on Industrial and Information Systems (ICIIS), Rupnagar, India, 2018, pp. 168-172, doi: 10.1109/ICIINFS.2018.8721421.

[14] S. Zhang, Z. Liang, W. Cao, Y. Gao and P. J. Pickhardt, "An Adaptive Boosting Strategy for GLCM-CNN Model in Differentiating the Malignant from Benign Polyps," 2019 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC), Manchester, UK, 2019, pp. 1-4, doi: 10.1109/NSS/MIC42101.2019.9060054.

[15] M. Ahsan, S. Naz, R. Ahmad, H. Ehsan, and A. Sikandar, “A Deep Learning Approach for Diabetic Foot Ulcer Classification and Recognition,” Information, vol. 14, no. 1, p. 36, Jan. 2023, doi: 10.3390/info14010036.

[16] M. Rahmawaty, H. A. Nugroho, Y. Triyani, I. Ardiyanto and I. Soesanti, "Classification of breast ultrasound images based on texture analysis," 2016 1st International Conference on Biomedical Engineering (IBIOMED), Yogyakarta, Indonesia, 2016, pp. 1-6, doi: 10.1109/IBIOMED.2016.7869825.

[17] Damle, A. "Comparing the Performance of CNN and MLP in Image Classification.

[18] L. Armi and S. Fekri-Ershad, ″Texture image analysis and texture classification methods - a review,″ International Online Journal of Image Processing and Pattern Recognition, vol. 2, pp. 1–29, 4 2019.

[19] E. A. Abbood, T. A. Al-Assadi, and E. A. Abbood, ″Glcms based multiinputs 1d cnn deep learning neural network for covid-19 texture feature extraction and classification,″ Karbala International Journal of Modern Science, vol. 8, 2022.

[20] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, "The Elements of Statistical Learning: Data Mining, Inference, and Prediction," vol. 2, pp. 1-758, Springer, 2009.

[21] S. P. Balamurugan, "A Comprehensive Study on MLP and CNN, and the Implementation of Multi-Class Image Classification using Deep CNN," in *Machine Learning and Deep Learning Techniques for Medical Science*, CRC Press, 2022, pp. 1-25.

[22] N. Coskun and T. Yildirim, "The effects of training algorithms in MLP network on image classification," Proceedings of the International Joint Conference on Neural Networks, 2003., Portland, OR, USA, 2003, pp. 1223-1226 vol.2, doi: 10.1109/IJCNN.2003.1223867.