RESEARCH ARTICLE OPEN ACCESS

Automated Detection of Infection in Diabetic Foot Ulcer Images Using CNN

Mrs. Roopa B S
Asst Prof
Dept of ECE
JNNCE, Shimoga
Email : roopabs@jnnce.ac.in

Sangeetha M S
Dept of ECE
sangeethams134@gmail.com

Sushmitha H Y
Dept of ECE
sushmithahy@gmail.com

Tanuja Pawar K P
Dept of ECE
tanujapawarkptanujapawarkp@gmail.com

Yashodha M R
Dept of ECE
yashodha.ramaradder@gmail.com

--************************----------------------------------

Abstract:

Diabetic foot infection (DFI), which results in reddish skin around the wound, is brought on by a bacterial or bone infection in the feet. The most common and harmful kind of diabetes mellitus is DFI. People who have kidney disease, eye disease, or a heart condition are most likely to experience it. Diagnosing a diabetic foot infection is done using the clinical manifestations of local inflammation. The infection has substantial clinical consequences for determining the chance of amputation when evaluating diabetic foot ulcers. A diabetic foot infection network (DFINET) is suggested in this study to evaluate infection and no infection from photos of diabetic foot ulcers. The unique parallel convolution layer with ReLU, the normalisation layer, and the fully linked layer are the 22 layers that make up a DFINETutilising a dropped connection. The DFINET has demonstrated promising results in the detection of infections, with an accuracy of 91.98% and a Matthews correlation coefficient of 0.84 on binary classification, when combined with this approach.Such improvements to existing approaches demonstrate how the suggested strategy can help medical professionals with automated DFI detection.

Keywords **—DFINET,CNN,DFI,DFU.**

--************************----------------------------------

I. INTRODUCTION

The most frequent cause of nontraumatic lower extremity amputation due to diabetes mellitus is probably diabetic foot infection, which requires treatment. Long-term exposure to cold and wet weather, wet feet, drinking alcohol, and smoking are all significant risk factors for acquiring foot infection. DFI is more prevalent in people with eye, kidney, or cardiac issues.Diabetes-related foot injury (DFI) is a serious typeof injury. When bacteria enter the body through a wound, this disease develops. Although diabetic foot ulcers (DFUs) do not typically cause infection, they frequently do. DFI, which causes the wound and surrounding skin to turn red, is brought on by bacteria or a bone infection in the location of the foot ulcer.Antibiotic therapy is used to treat diabetic foot infection. Infections can spread if a medical expert does not treat the wound, which could result in pain, discomfort, necrosis, and, in the worst case scenario, amputation. Peripheral artery disease (PAD) and neuropathy are the two main causes of diabetic foot infection . Leg sensation can suffer severely from neuropathy (nerve injury) . A person who cannot feel the discomfort runs the danger of getting an infection in their feet. It can make the body more open to bacteria that are weak.Another reason for diabetic foot infections is PAD, which slows or stops the healing process by obstructing blood flow. People risk developing a foot infection because they won't feel the initial injury.

DFI is identified by a physical examination, blood testing, and a leg Doppler investigation. The doctor will examine the foot to check for indications of a foot infection. before that, the Traditional procedures take a long time and are quite expensive. In patients with active DFU and ischemia, infection should be investigated. Amputation of a foot or limb occurs in 20% of infections, affecting roughly 56% of DFU. The International Diabetes Federation estimates that 80% of people with diabetes mellitus (DM) reside in low-income nations, including India, the second-largest diabetes country in the world after China. In India, there are approximately 69.1 million people with DM, with a prevalence rate of 9.3% . A diabetic patient with a "high-risk" foot requires frequent medical visits, pricey medicine, and other costly procedures to prevent the catastrophic complications described above personal hygiene measures.

Patients and their families are consequently put under a heavy financial strain, especially in undeveloped countries where the cost of therapy is substantial. For the screening of DFI, there aren't many computer-aided procedures accessible. A crucial first step in creating an extensive computerised DFU evaluation system for remote monitoring is to identify infection in DFU using affordable machine learning methods. Therefore, it is crucial to create DL algorithms to analyse foot ulcer images and determine whether or not patients are infected.

The doctor will benefit from the most recent developments in computer vision (CV) and deep learning (DL) in recognising foot infection for additional therapy.

The inspiration from earlier research works serves as the foundation for the unique framework for DFI classification proposed in this study. The proposed CNN model incorporates features from parallel convolution layers for compact representation and because the features contain particular and essential information regarding foot infection. Combining all of these factors has the benefit of enabling researchers to learn more about the infection and improve treatment of diseases that resemble healthy skin. To discriminate between infection and non-infection classes, many CNN models were trained. Then, we demonstrated how employing the suggested model parameters enhances overall classification.

II. RELATED WORK

The majority of imaging-related issues as well as issues with diagnosing diseases including Alzheimer's, cervical cancer, malaria, and brain tumours have been resolved thanks to the development of DL and CV in medicine [7,8]. A DFU infection is characterised by at least two of the traditional purulence symptoms. Although it is challenging to determine whether diabetic foot infections are present from DFU images, growing redness in and around the ulcer as well as coloured purulence may be indicators of DFI. The most reliable diagnostic procedure in the medical system is blood testing. Additionally, the debridement of necrotic and devitalized tissues, which eliminates a crucial indicator of infection in DFU, occurred after the images in this dataset were captured. The ensemble DL model was suggested by Rostami et al. [4] to determine the wound images from many sources. Six categories—normal, normal skin, venous wound, diabetic wound, pressure, and surgical wound—are categorised by the suggested model. The model had a multilevel classification accuracy of 87.70% and a binary classification accuracy of 94.28%. A model for the prognosis of DFU using thermal imaging was put forth by Kim et al. The feature extractor is the ResNet50 model, while the classifiers are the machine learning (ML) classifiers random forest and support vector machine (SVM). The model had a maximum accuracy of 81.1%. The CNN architecture described by Das et al. includes a deep residual block to extract the high-level features, and the components are subsequently merged with variousalgorithmic learning processes.

Only two models are available for recognising diabetic foot infections, according to the literature. In the current study, DL algorithms for DFI recognition are examined while taking a literature analysis into account. A new convolutional neural network (CNN) was created utilising diabetic foot photos from scratch to overcome the difficulties encountered in detecting infection and non-infection due to inadequate illumination, poor contrast, markings, and skin tone.

A list of important contributions to this study is shown below:

1) To increase the classification accuracy in predicting infection and non-infection (2), a 22-layer CNN architecture including convolution layers, batch normalisation, ReLU, and a dropout layer is proposed.
2) To improve the performance of the suggested model, the hyperparameters are researched and adjusted.

III. PROBLEM STATEMENT

The goal is to create a CNN -based automated method for identifying infection in DFU images. DFU photos should be submitted into the system, which should then categorise them as infected or non-infected. The system should be able to accurately identify different infection-related symptoms like redness, swelling, and discharge. Additionally, the system needs to be built to be resilient to changes in patient demographics, image quality, and lighting.

IV. BLOCK DIAGRAM

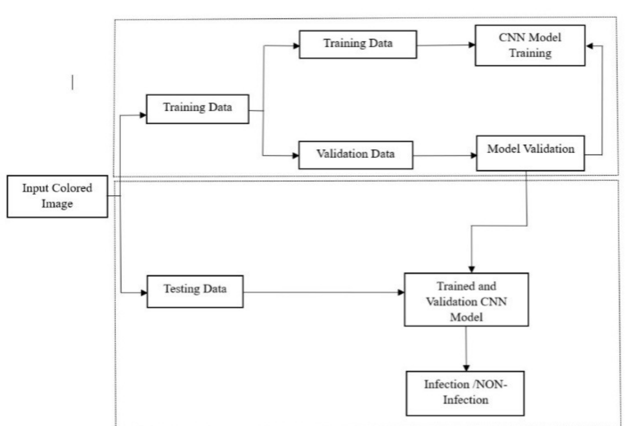

Figure 1. Block Diagram

V. MATERIALS AND METHODS

The proposed model is developed to effectively extract the discriminative characteristics from images of diabetic foot ulcers by improving overall performance in recognising infection and non-infection.

Dataset for the Study: Despite being inaccessible to the general public, the DFU photos with the infection can be accessed with the correct procedures. The dataset is assessed once the main researcher signs a dataset release agreement. There are two subclasses for each of the two classes in the dataset: infection versus non-infection and ischemia versus non-ischemia. This study contrasts infections and non-infections to improve the overall categorization performance. The collection consists of 5890 images in total, 2945 of which include ground truth labels for infection and 2945 of which do not.

Final designations for the ground truth were made by a senior physician. Figures 1(a) and 1(b), which depict images from the dataset indicating the infection and non-infection classes, respectively.

Methodology: The main flow of the suggested technique is shown in Figure 3. Testing and training sets (training and validation sets) are separated from the augmented dataset.

The trained model is tested on a test set, and then infection and non-infection are detected using DFU images. The projected DFINET model is shown in Figure 4 along with a description of each layer. The model consists of 22 layers make up the model: 10 convolutional, 5 max-pooling, 5 normalisation, and 2 fully linked layers. The suggested approach uses the ReLU activation function in the convolutional layer to map negative values to 0 and positive values to a maximum value of z. The ReLU function can be calculated using equation (1), where z is the neuron's input.

$$F(z)=\text{maximum}(0,z) \qquad (1)$$

The normalisation layer expedites training by normalising the feature values using the mean and variance of the input for each channel. The output of the two blobs are combined via concatenated layers into a single blob. Following feature concatenation, the feature representation and computational cost are minimised using maximum pooling. The flattened layer is paired with the fully linked layer to convert 2-dimensional data to 1-dimensional data. By multiplying the input by the weight value at each node from the flattened layer and then by the bias value, the fully connected layer produced the output value.The dropout layer with a probability of dropout is used by the fully linked layer. The dropout function lessens overfitting, making the suggested model more broad.

$$\sigma(z_i) = \frac{e^{z}i}{\sum_{j=1}^{k} e^{z_j}} \quad (2)$$

Here, Z=(z1,z2,...,zk) and i=1,2,3,...,k
Using the training dataset, the DFINET model discovers the patterns that distinguish infections from non-infections, potentially enhancing its performance.
The proposed model's precise parameters are provided in Table 2.Where NF = Number of Filtes and KS = Kernal Size.

Layer type	**Layer Parameter**
Conv_1	KS = 7 × 7, NF = 64
Max_pool_1	KS=3×3,Stride=2
Conv_2	KS =3×3, NF=64
Conv_3	KS=3×3, NF=128
Max_pool_2	KS= 3×3, Stride =2
Conv_4a	KS =3 × 3, NF -= 128
Conv_4b	KS = 1 × 1, NF = 128
Max_pool_3	KS = 3 × 3, Stride = 2
Conv_5a	KS = 3 × 3, NF = 128
Conv_5b	KS = 1 × 1, NF = 128
Conv_6a	KS = 3 × 3, NF = 256
Conv_6b	KS = 1 × 1, NF = 256
Max_pool_4	KS = 3 × 3, Stride = 2
Conv_7a	KS = 1 × 1, NF = 256
Max_pool_5	KS = 7 × 7, Stride = 2
FC_1	100
Dropout	Probability = 0.3
FC_1	2
Total number of parameters	14, 895, 440

Adam the Optimizer: During the training phase, the proposed model adjusts its weights using the Adaptive Moment Estimation (Adam) optimizer. Adam uses both the running average of the gradients and the second moments of the gradients.
Adam utilises less memory and is a fairly efficient computer user. For each parameter, WJ weight updates are delivered via

$$\Delta\omega_t = -\eta \frac{v_t}{\sqrt{s_t + \varepsilon}} * g_t, \quad (3)$$

$$\omega_{t+1} = \omega_t + \Delta w_t \quad (4)$$

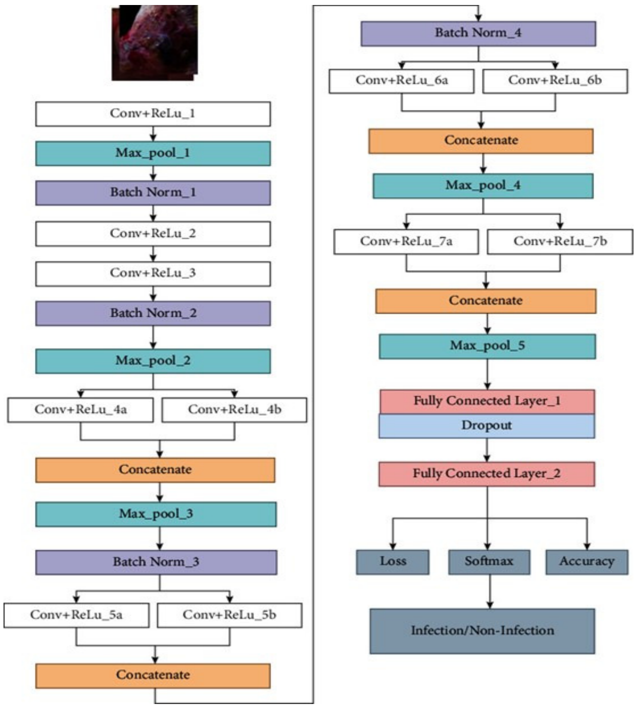

Figure 2: Architecture

V.RESULTS

The acquired dataset is divided into three separate training and testing sets at random.The same parameter, which is set to a training epoch of 75, is used to train both DFINET and AlexNet. in terms of exactness and precision. The training validation plot for the DFINET and AlexNet models is shown in Figure 1 and Figure 2. DFINET achieved a validation accuracy of 98.00% compared to AlexNet's 79.31%. The validation accuracy and validation loss are plotted for each epoch. After the models have been verified on the validation dataset, they are tested on the testing dataset. The confusion matrix is created using the results of the model testing.

DFINET classification results for correctly and wrongly categorised pictures. The confusion matrix provides a clear picture of the model's effectiveness as a classification tool. The DFINET and AlexNet models' performance values are computed using the confusion matrix. The suggested DFINET performed remarkably well in classifying different types of infections and non-infections.The DFINET model obtains a 98.00% accuracy in 75 epochs.

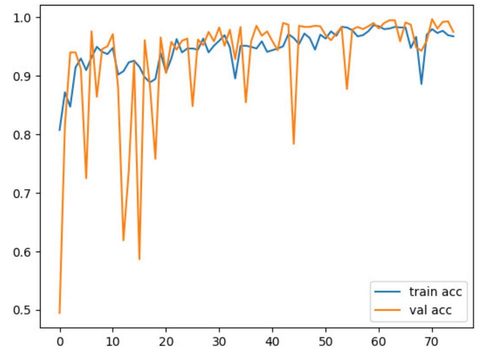

Figure3: Accuracy.

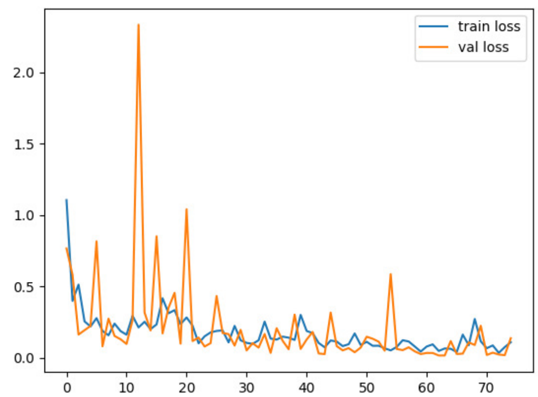

Figure4: Loss

Compared Model: AlexNet

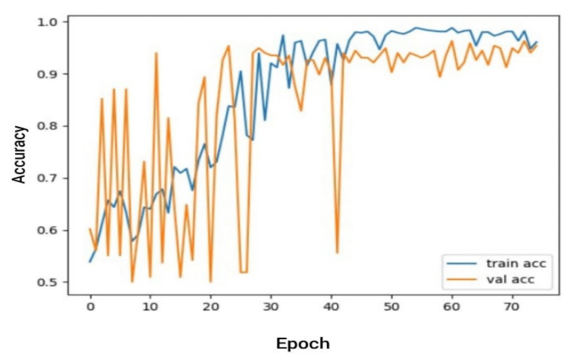

Figure 5: Alexnet Accuracy

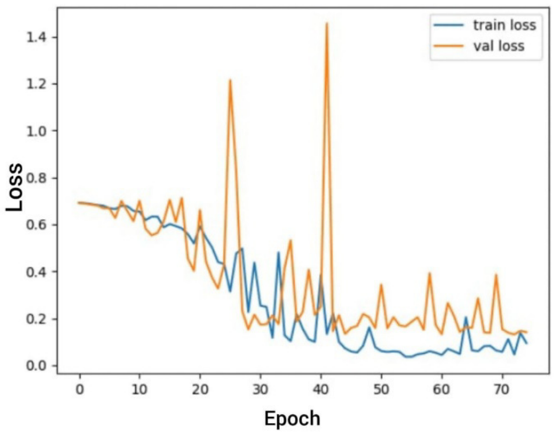

Figure 6: Alextnet Loss

VI. CONCLUSION

In order to discriminate between classes of infections and non-infections from the DFU images, this study suggests and trains the CNN-based models DFINET and AlexNet. The suggested DFINET has produced encouraging results when compared to the pretrained model. The DFINET allows doctors to diagnose infection in DFU more rapidly and laboriously. It also assists in creating a suitable treatment plan for patients to prevent amputation. The performance of these strategies could be enhanced in the future with better and more balanced data. The performance of the algorithms on this dataset could be improved by further modifying the deep learning hyperparameters.The development of telemedicine as a field of technology can be helped by the DFI screening-specific online and mobile application.

REFERENCES

[1] "Automated Detection of Infection in Diabetic Foot Ulcer Images Using CNN", J. Yogapriya, Venkatesan Chandran, M. G. Sumithra, B. Elakkiya, A. Shamila Ebenezer, and C. Suresh Gnana Dhas, Journal of Healthcare Engineering, 2022.

[2] M. H. Yap, R. Hachiuma, A. Alavi et al., "Deep learning in diabetic foot ulcers detection: a comprehensive evaluation," Computers in Biology and Medicine, vol. 135, 2021.

[3] S. K. Das, P. Roy, and A. K. Mishra, "Fusion of handcrafted and deep convolutional neural network features for effective identification of diabetic foot ulcer," Concurrency and Computation: Practice and Experience, vol. 34, 2022.

[4] B. Rostami, D. M. Anisuzzaman, C. Wang, S. Gopalakrishnan, J. Niezgoda, and Z. Yu, "Multiclass wound image classification using an ensemble deep CNN-based classifier," Computers in Biology and Medicine, vol. 134, 2021.

[5] J. Husers, G. Hafer, J. Heggemann et al., "Automatic classification of diabetic foot ulcer images - a transfer-learning approach to detect wound maceration," Studies in Health Technology and Informatics, vol. 289, pp. 301–304, 2022.

[6] S. K. Das, P. Roy, and A. K. Mishra, "Recognition of Ischaemia and infection in diabetic foot ulcer: a deep convolutional neural network based approach," International Journal of Imaging Systems and Technology, vol. 32, 2021.

[7] M. Suriya, V. Chandran, and M. G. Sumithra, "Enhanced deep convolutional neural network for malarial parasite classification," International Journal of Computers and Applications, vol. 0, no. 0, pp. 1–10, 2019.

[8]] S. Murugan, C. Venkatesan, M. G. Sumithra et al., "DEMNET: a deep learning model for early diagnosis of alzheimer diseases and dementia from mr images," IEEE Access, vol. 9, pp. 90319–90329, 2021.

[9] R. B. Kim, J. Gryak, A. Mishra et al., "Utilization of smartphone and tablet camera photographs to predict healing of diabetes-related foot ulcers," Computers in Biology and Medicine, vol. 126, Article ID 104042, 2020.