Detection of Diabetic Foot Ulcer from Kaggle datasets using LBP and LIPC Methods

Prakash R V[1], Dr. K Sundeep Kumar[2]

[1]Research Scholar & Assistant Professor, Department of CSE, S.E.A. College of Engineering & Technology, Bangalore, Visvesvaraya Technological University, Belagavi
[2]Professor & Head, Department of CSE, S.E.A. College of Engineering & Technology, Bangalore, Visvesvaraya Technological University, Belagavi

ABSTRACT

The identification of Diabetic Foot ulcers is critical for patients' early diagnosis and therapy planning. Image processing algorithms have developed as useful tools for automatic and reliable ulcer diagnosis from medical imaging data in recent years. This research describes a novel approach for detecting Diabetic Foot ulcers using image processing techniques. A series of preprocessing processes are used in the proposed method to improve the quality of Diabetic Foot pictures and reduce noise. Image scaling, noise reduction, and contrast improvement are all included. Following preprocessing, image segmentation algorithms are used to isolate probable ulcer locations and separate the Diabetic Foot region from the backdrop. Various feature extraction approaches are used to extract significant features from the segmented Diabetic Foot regions for ulcer identification. These criteria capture crucial ulcer properties such as form, texture, and intensity fluctuations. The retrieved features are then used to train a classifier to distinguish between ulcer and non-ulcer regions. Experiments are carried out using a Kaggle dataset of Diabetic Foot pictures encompassing both ulcer and non-ulcer instances to assess the efficacy of the suggested technique. The findings show that the proposed method for detecting Diabetic Foot ulcers is highly accurate and efficient. Comparisons with existing approaches demonstrate the suggested method's advantages in terms of detection accuracy and computing efficiency. Overall, the suggested image-based Diabetic Foot ulcer detection system has significant promise for supporting medical professionals in the early detection of Diabetic Foot ulcers. It has the potential to improve patient outcomes by allowing for timely intervention and personalized treatment regimens.

Keyword*: Diabetic Foot Ulcer, LBP, LIPC*

1. INTRODUCTION

Employing magnetic resonance imaging for medical diagnostics Because the outcome is so crucial to patient care, prediction algorithms' robustness and accuracy are extremely vital. One of the key steps in surgery and therapy planning is Diabetic Foot ulcer segmentation. However, in clinical practise right now, the majority of Diabetic Foot ulcer segmentation in Diabetic Foot ulcer pictures is done manually. Manual Diabetic Foot ulcer delineation takes a lot of time, is challenging, and is operator-dependent. Thresholding, edge detection, and morphological approaches are examples of low-level procedures that are quick and simple to modify. However, the effectiveness of these approaches for ulcer segmentation heavily rely on the presence of a clear disparity in intensities between ulcer and non-ulcer zones. Simple growth methods for watersheds and regions regularly result in full borders. However, like with the intensity-based strategy, both two techniques are susceptible to noise. Furthermore, due to the weak and dispersed edges brought on by edoema, the majority of intensity-based approaches have a tendency to over segment ulcers. The mid-sagittal plane of the healthy human Diabetic Foot is generally symmetrical. Based on the idea that malignancies might produce asymmetry between the left and right cerebral hemispheres when they develop in one of the cerebral hemispheres, the asymmetric analytic approach for ulcer segmentation was developed. Ulcers can be generally localised in the appropriate Diabetic Foot hemisphere when this imbalance is found.

Due to the fact that ulcer segmentation is carried out in one of the cerebral hemispheres, the asymmetric analysis approach can speed up the process of ulcer identification and segmentation. However, locating the mid-sagittal plane

precisely requires effort and time. More significantly, when a malignancy is positioned across the mid-sagittal plane, asymmetry analysis might not be helpful. Methods for segmenting an atlas have been thoroughly studied. By comparing the differences between aberrant and normal Diabetic Foots, Diabetic Foot atlases can collect crucial information prior to ulcer segmentation enhancement. However, due to the intensity changes surrounding the ulcer generated by edoema and the deformations of healthy tissue shape induced by the mass impact of the disease, the deformable registration of the Diabetic Foot atlas to Diabetic Foot pictures with ulcer is a very difficult process. Affinity registration was employed in a prior work to match the atlas to the ulcer imaging data. The misalignment difficulties are recognised on the aligned atlas when a considerable Diabetic Foot structural distortion develops, which may greatly reduce segmentation accuracy. The 2-D/3-D data segmentation for ulcer has frequently utilised the contour/surface evolution approach. This approach may be expressed either as an active contour model/snake function or intuitively as a level set function.

The level set technique can describe contours with complicated topology and manage topological changes, such as splitting and merging, in a natural and effective manner as compared to the parametric active contour model. Furthermore, the level set approach may easily be extended to 3D without the need for extra equipment. Even when 3-D level set surfaces are employed, the initializations and tuning of the parameters are difficult to identify with the contour/surface evolution approach. Among interactive algorithms, the Graph-based Seeded Segmentation Framework is one of the most often used techniques. A global optimisation method that shown exceptional performance for ulcer segmentation is called graph-based seeded segmentation. The manual seed selection required by this procedure makes it challenging to discriminate between the many ulcerous tissues while choosing the first seeds for the various tissues. A cellular automata-based seeded technique for Diabetic Foot ulcer segmentation has been introduced in a prior work and is known as ulcer-cut. With this technique, the user merely needs to trace a line around the diameter of the largest visible malignancy. The approach may not include all ulcer locations inside the volume of interest along the depth direction, resulting to ulcer under segmentation, even though this initial seed selection strategy might reduce operator engagement and lessen the algorithm's sensitivity to initialization. In recent years, the segmentation of Diabetic Foot ulcers has been a common application of unsupervised learning techniques like k-means and fuzzy clustering.

The fuzzy approach is a powerful tool for medical image processing since it takes into account that medical pictures are naturally hazy. A training phase is not necessary for the fuzzy technique to collect pixel proximity within the same goal region. However, the majority of fuzzy approaches perform poorly when trying to segment non-enhanced malignancies and only perform well for ulcers that show hyper-intensity. The reason for these circumstances is that these fuzzy approaches frequently include intensity-based pre- or post-processing techniques, such as thresholding and morphological procedures. In ulcer segmentation, the supervised classification learning approach is frequently utilised. The label of each voxel in a testing volume may be estimated by well-trained classifiers, which can also extract discriminative information from the training data. Traditional classification techniques, on the other hand, divide each voxel into distinct groups without taking into account the spatial connection between the current and surrounding voxels. This approach might not produce a fully optimised outcome. A classification approach and a regularisation step are typically used together to overcome this issue. You can accomplish the regularisation step by modelling the boundary or by using an MRF/CRF variation of a random field spatial prior. In the earlier investigations, tissue-specific Gaussian mixture models' probabilities and context-aware spatial characteristics were employed as classifier inputs to generate satisfactory segmentation results without the need for posthoc regularisation. For the purpose of segmenting Diabetic Foot ulcer without the need of explicit regularisation, we suggest a brand-new classification technique called local independent projection-based classification (LIPC).

2. LITERATURE SURVEY

Following is the work done carried out in various article by the authors
Accurate detection of Diabetic Foot ulcer using optimized feature selection based on deep learning techniques - 2023 Springer- A Diabetic Foot ulcer is an unexpected growth of nerves inside the Diabetic Foot that interferes with the Diabetic Foot's normal function. Numerous lives have been lost as a result of it. It will take time to save people from this disease by prompt discovery and the appropriate treatment. It takes a lot of effort and time to locate ulcerous cells in the human Diabetic Foot. However, detecting Diabetic Foot ulcers with the precision and speed necessary is a significant difficulty in the field of image processing. This study suggests a brand-new, precise, and well-designed approach to identify Diabetic Foot ulcers. Preprocessing, segmentation, feature extraction,

optimisation, and detection are some of the processes the system uses. For picture segmentation, threshold and histogram approaches are used. For feature extraction, the grey level co-occurrence matrix (GLCM) is utilised. Here, the optimised convolution neural network (CNN) method is used, which selects the best features by using the whale and grey wolf optimisations. The CNN classifier is used to detect Diabetic Foot ulcers. Using accuracy, precision, and recall characteristics, this system compares its performance with that of another contemporary optimisation approach and declares that its work is superior. Python is the programming language used to create this system. This technique has been optimised to identify Diabetic Foot ulcer with an accuracy of 98.9%.

Diabetic Foot Ulcer Detection and Classification Using Intelligence Techniques: An Overview-2023 IEEE- Rapid and uncontrolled cell development in the Diabetic Foot is the hallmark of a malignancy. It might be deadly if it is not treated in the early stages. Accurate segmentation and classification remain difficult despite multiple large efforts and good results. The differences in ulcer site, shape, and proportion make the detection of Diabetic Foot malignancies substantially more difficult. The primary objective of this study is to provide researchers with complete literature on the capability of Magnetic Resonance (MR) imaging to detect Diabetic Foot ulcers. This study suggested numerous methods to identify malignancies including Diabetic Foot ulcer using computational intelligence and statistical image processing approaches. Additionally, the study displays an evaluation matrix for a certain system employing specified systems and dataset kinds. The anatomy of Diabetic Foot ulcers, available data sources, augmentation techniques, component extraction, and classification of Deep Learning (DL), Transfer Learning (TL), and Machine Learning (ML) models are also covered in this article. Finally, our study includes all pertinent information regarding ulcers, including its advantages, disadvantages, improvements, and future developments.

A Deep Analysis of Diabetic Foot Ulcer Detection from MR Images Using Deep Learning Networks - 2023 MDPI- The goal of artificial intelligence (AI) is to build machines that function and behave like people. Pattern recognition, planning, and problem-solving are just a few of the activities that computers can perform using artificial intelligence. In machine learning, a class of algorithms known as "deep learning" is employed. Deep learning is used to develop models for the identification and classification of Diabetic Foot ulcers using magnetic resonance imaging (). This makes it possible to quickly and easily identify Diabetic Foot ulcers. The majority of Diabetic Foot problems are caused by abnormal Diabetic Foot cell growth, which can damage the Diabetic Foot's structure and ultimately lead to malignant Diabetic Foot ulcer. The likelihood of mortality may be reduced by early detection of Diabetic Foot ulcers and following adequate treatment. In this article, we propose a convolutional neural network (CNN) architecture for accurate Diabetic Foot ulcer detection from MR images. In addition, this study analyses a number of models, including ResNet-50, VGG16, and Inception V3, and compares them to the suggested design. We looked at a variety of measures, including accuracy, recall, loss, and area under the curve (AUC), to evaluate how well the models performed. We came to the conclusion that the suggested model outperformed the others after comparing them to other models and our own using these measures.

Diabetic Foot Ulcer Detection using Decision-Based Fusion Empowered with Fuzzy Logic –2022 Hindawi- One of the most deadly and terrible illnesses on the earth is Diabetic Foot ulcer. An infected person's Diabetic Foot contains it in the form of unregulated and abnormal cells. If glioblastomas are not detected early, over 60% of them progress to into big ulcers. On the whole, performance might be better, however there is some excellent material on ulcer diagnosis. Early illness diagnosis in the medical field has been greatly aided by machine learning (ML)-based approaches. The performance of the Diabetic Foot ulcer detection process may be enhanced by the employment of ML approaches in combination with better image-guided technologies. An ML-based method for detecting Diabetic Foot ulcer is given in this paper. Fuzzy logic is used with the support vector machine (SVM) and adaptive back propagation neural network (ABPNN) methods. Fuzzy logic is employed to combine the outcomes of ABPNN and SVM. The BRATS dataset was used to build the suggested method. According to experimental findings, the ABPNN model has an accuracy rate of 98.67% during training and 96.72% during testing. In contrast, the SVM model achieved accuracy levels of 97.70% and 98.48% during the training and testing periods. The total accuracy of the suggested approach reaches 98.79% for the training phase and 97.81% for the testing phase after implementing fuzzy logic for decision-based fusion.

Diabetic Foot Ulcer Segmentation and Survival Prediction using Multimodal Scans with Deep learning Algorithms – 2022 IEEE- Diabetic Foot ulcers are the result of aberrant Diabetic Foot cell proliferation. The two main categories of medical imaging equipment are and CT, which are frequently used to scan Diabetic Foot ulcers. The internal parts of the Diabetic Foot are scanned using imaging. Diabetic Foot ulcers come in two flavours:

benign and malignant. While a malignant Diabetic Foot tumour cannot be cured, a benign Diabetic Foot tumour may often be treated. Malignant Diabetic Foot ulcers include gliomas and astrocytomas. a radiologist identifying and diagnosing a Diabetic Foot ulcer using traditional methods. Errors and delays happen much too frequently. Imaging technicians are unable to classify and separate the many Diabetic Foot tumour pictures that neurosurgeons produce manually.

3.   EXISTING AND PROPOSED SYSTEM

EXISTING SYSTEM: In the processing of digital images, segmentation is the procedure used to separate the portions. One of the common disorders that is managed by medical technology is Diabetic Foot ulcer. Early Diabetic Foot ulcer detection can strengthen the preventative mechanism to a greater extent. One of the most crucial aspects of the job is using digital image processing tools to find Diabetic Foot ulcers. We will separate the Diabetic Foot ulcer region for digital photographs as part of our investigation. Doctors have used the magnetic resonance imaging () method to find Diabetic Foot ulcer. Finally, using the ROI approach, we will identify the presence of Diabetic Foot ulcer in the picture. We will then continue with the quantization process for images and concentrate on clustering processes of various detecting areas of the Diabetic Foot.

make judgements based on local pixel information and work well when the object's intensity levels fall clearly beyond the background's range of values. To record significant events and changes in the world's attributes, abrupt variations in picture brightness must be detected. It may be demonstrated that picture brightness discontinuities exist under rather broad assumptions for an image creation model. In order to divide the image into related sections, nearby pixels with the same intensity levels are grouped together. Then, adjacent areas are combined using a criteria that may take into account the homogeneity or sharpness of region borders. Overly strict standards lead to fragmentation; too-loose standards ignore muddled borders and over-merge Clustering divides data instances into subsets in a way that groups together comparable examples while separating dissimilar instances into various groups. Typically referred to as the active contour model, it iteratively adjusts an initial boundary shape represented by spline curves by performing different shrink/expand operations in accordance with an energy function. The energy-minimizing model is not novel, but it takes on an intriguing new twist when coupled with the maintenance of a "elastic" contour model. As is typical with such techniques, one must protect against the possibility of becoming stuck in a local minimum; this is no simple feat. In order to combine nearby single pixel segments into one segment, several segmentation merging techniques employ a technique called region expanding. Growing a region requires a set of seeds, or initial pixels13. Picking a seed from the set, analysing all of its four linked neighbours, and merging appropriate neighbours to the seed make up the region-growing process. After that, the seed is taken out of the seed set and all merging neighbours are added. Up until the seed set is completely empty, the area continues to expand.

Region splitting is a divisive strategy whereas region merging is an agglomerative strategy. The merging of two segments is simple, but the splitting of a segment necessitates the creation of suitable sub-segments into which the original segment may be divided, as we previously discussed. Consequently, the two techniques don't solve fundamentally distinct issues, as we previously stated, but rather present them in different ways. Naturally, the question of how to divide a segment into smaller parts is a segmentation issue, and we may approach it as such. Any segmentation technique can be used to divide the segment into smaller parts. There is no inherent difference save the hierarchical level.

PROPOSED SYSTEM: The project proposes a segmenting and detecting ulcer by using spatial fuzzy clustering algorithm for Magnetic Resonance () images to detect the Diabetic Foot Ulcer. A novel classification framework is derived by introducing the local independent projection into the classical classification model. Locality is important in the calculation of local independent projections for LIPC The artificial neural network is used to classify the stages of Diabetic Foot Ulcer then it is trained network. Morphologic contents of frequently require segmentation of the image volume into tissue types. Manual segmentation also shows large intra- and inter-observer variability For example, accurate segmentation of MR images of the Diabetic Foot is of interest in the study of many Diabetic Foot disorders. The proposed method consists of four major steps, i.e., pre-processing, feature extraction, ulcer segmentation using the LIPC method, and post processing. To reduce computational costs, we embedded the proposed method in a multiresolution framework. The qualitative results of the proposed method with the learned softmax regression model on different data groups. Parameters k, N, and w were set to 10, 40 000, and 5, respectively, for each class at each level. The ulcer boundaries of the real patient data were more blurry than those of the synthetic data. Therefore, the ulcer classification performance was better in the synthetic data than that in the real patient data. The edema boundaries of both real patient data and synthetic data were quite blurry, which led to

more inaccurately classified voxels in the edema regions than those in the ulcer regions. Two other typical segmentation results using the proposed method. That the ulcer boundary of low-grade real patient data was more blurry than that of high-grade real patient data. The edema region was also blurry in low-grade real patient data.

4. DESIGN METHODOLOGY

Thus, the classification accuracy of the ulcer and edema in the low-grade patient data was lower than those in the high-grade patient data. To evaluate the Effectiveness of LIPC, both SRC and LIPC used LAE as the coding method. Moreover, the classification scores were computed. For LIPC, parameters k, N, and w were set to 10, 40 000, and 5, respectively, for each class at each level. For SRC, a dictionary containing samples from three classes was constructed for each level. This dictionary consisted of three sub dictionaries and each sub dictionary corresponded to a class. For a fair comparison, the size of each sub dictionary was set to 40 000. Therefore, the size of the dictionary for SRC was 120 000 at each level. The number of nonzero values in LAE for SRC was determined as follows. We first randomly selected 10 000 samples from the training data for each class at each level and computed the reconstruction error norms of all the selected samples using the dictionary. The number of nonzero values in LAE was varied from 5 to 1,200. Finally, the minimum reconstruction error was found when the number of nonzero values was set to 1000. After we investigated the results of different data groups, the mean DS of LIPC was 5.3% higher than that of SRC. The classification results with LIPC and SRC on different data groups are displayed, which shows that the proposed LIPC could be effectively used in ulcer segmentation.
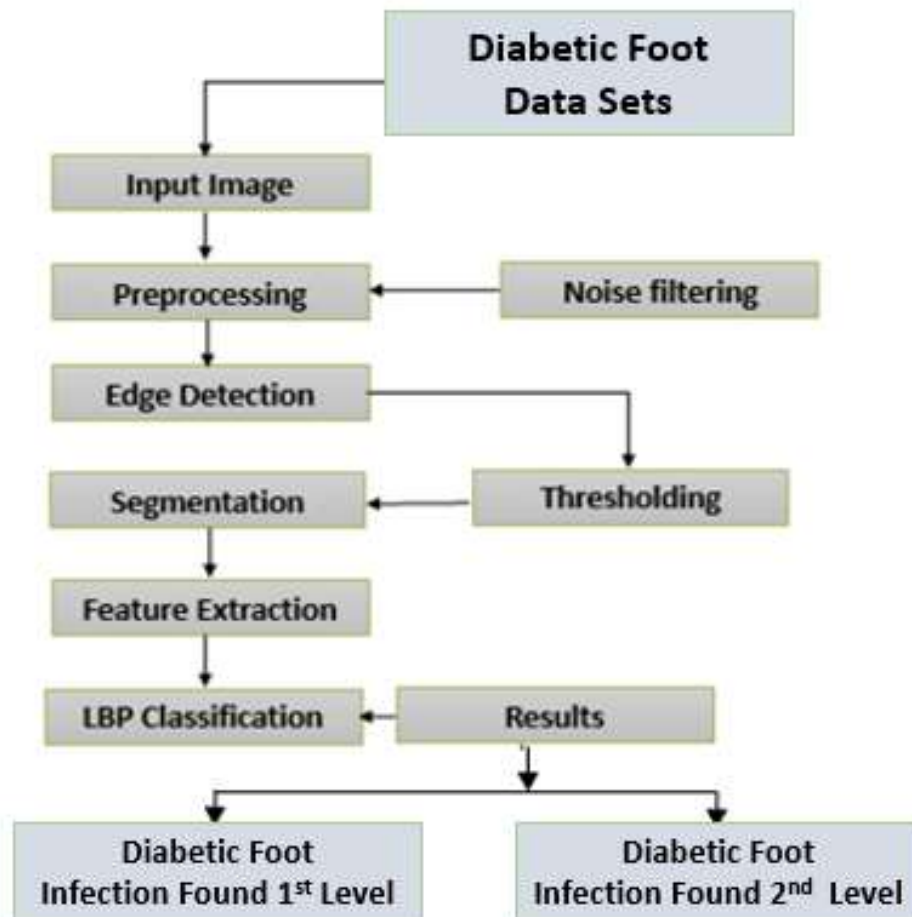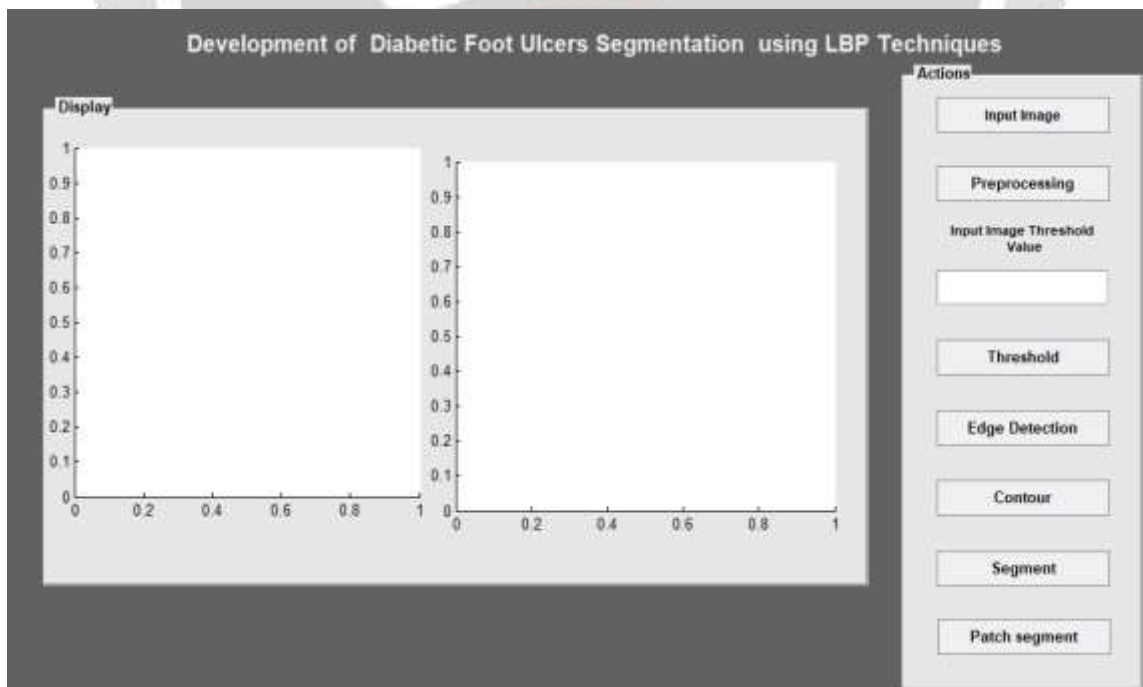

Fig. 4.1: system architecture of development of Diabetic Foot ulcer stages detection of datasets using machine learning algorithm

5. RESULTS AND DISCUSSION

Following screenshots of Diabetic Foot ulcer detection using LBP algorithm. Figure 5.1 shows the various datasets used for processing.

Fig 5.1: Diabetic Foot data sets for the development Diabetic Foot ulcer detection using LBP algorithm

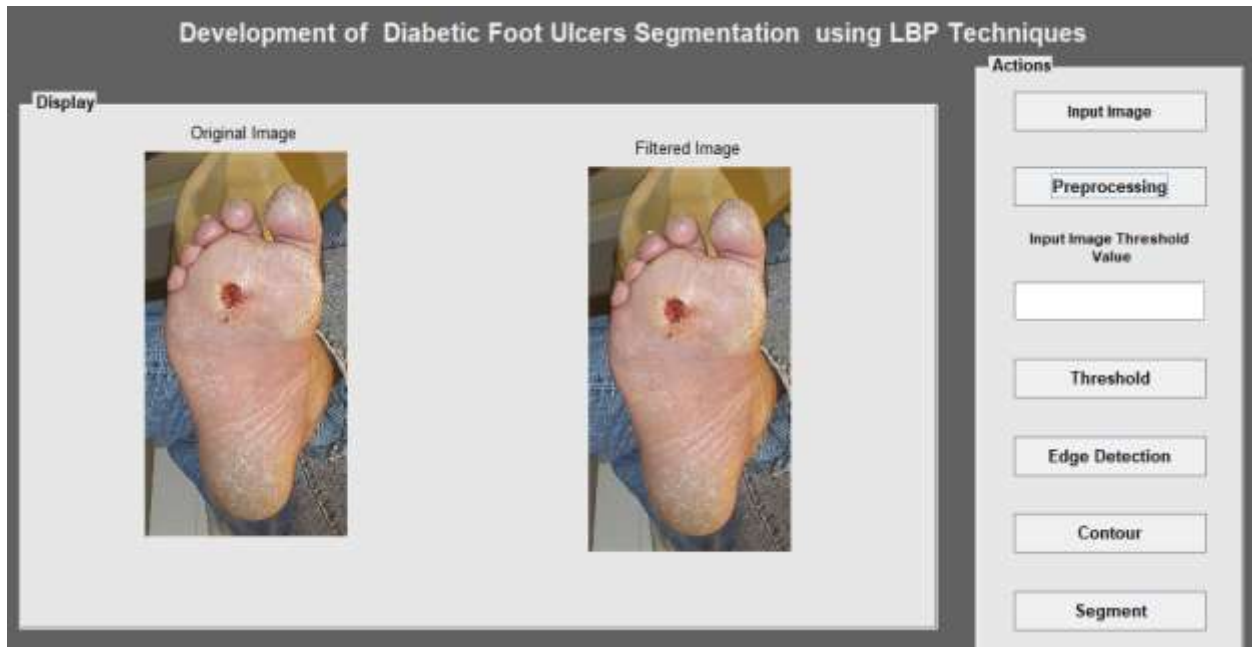**Fig 5.2: GUI of development of Diabetic Foot ulcer detection using LBP algorithm**

Fig 5.3: Illustration of filtered image and thresholding for development of Diabetic Foot ulcer detection using LBP algorithm
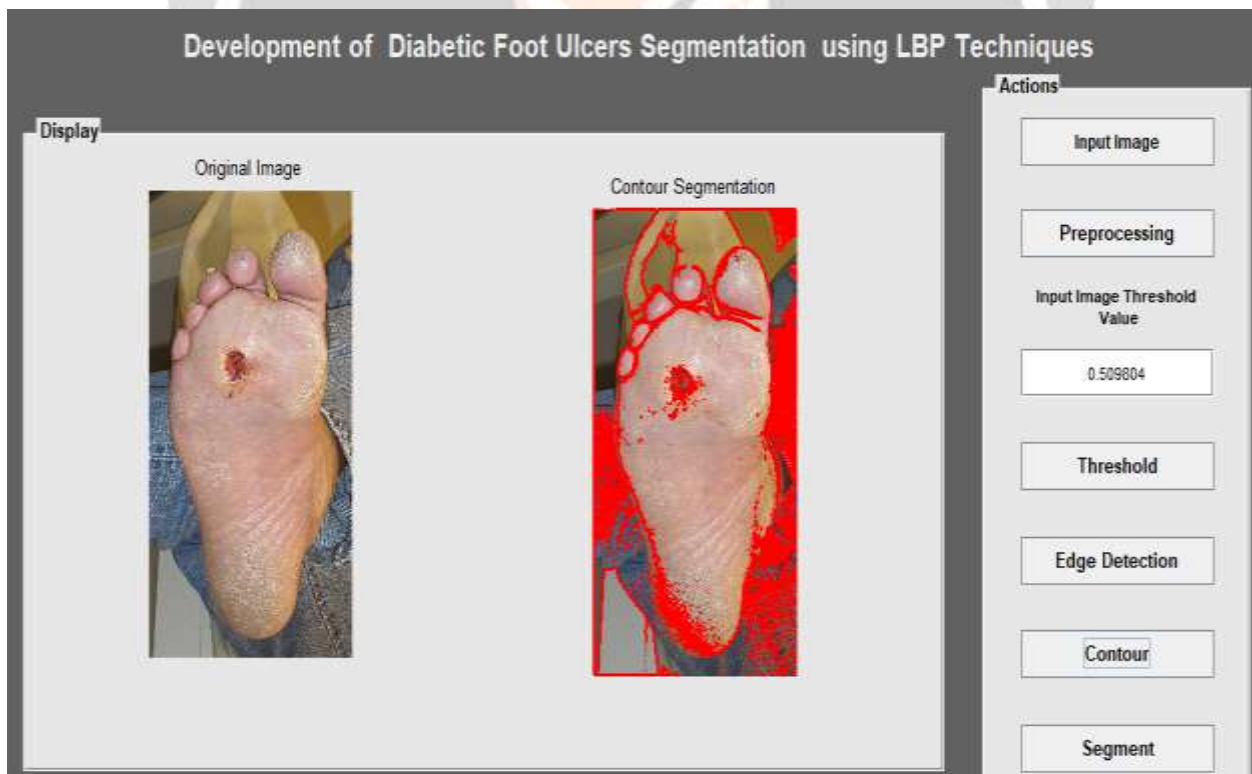

Fig 5.4: Contour representation of development of Diabetic Foot ulcer detection using machine learning algorithm
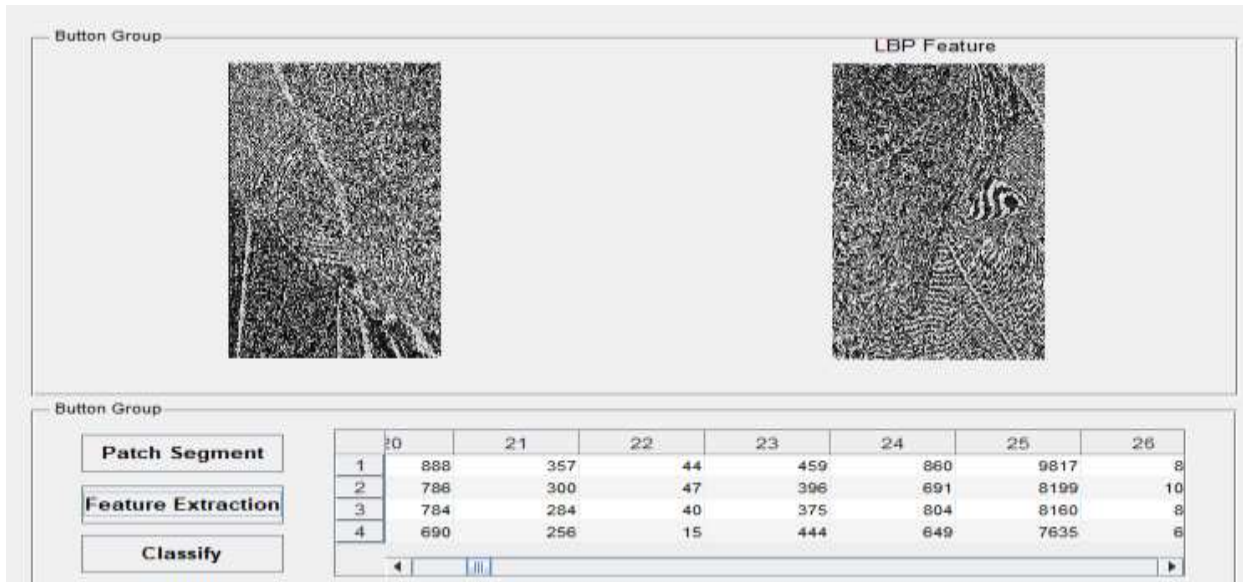
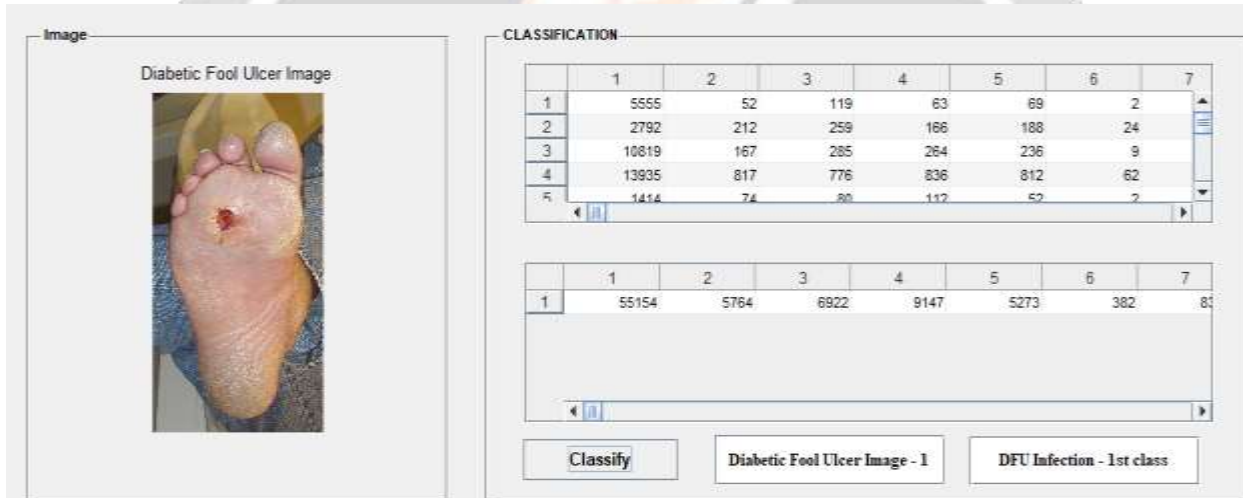**Fig 5.5: LBP feature extraction for development of Diabetic Foot ulcer detection using LBP algorithm**

Fig 5.6: Ulcer stage output FIRST CLASS – Early-Stage detection for development of Diabetic Foot ulcer stages detection of datasets using machine learning algorithm

6. CONCLUSION

Hence, we introduce new method to Segment the Diabetic Foot ulcers and classify the image is normal or abnormal. Simulation results shows that our Classifier and segmentation outperforms than other Techniques. An automatic method is proposed for Diabetic Foot ulcer segmentation in images. An LIPC-based method was introduced to solve the ulcer segmentation problem. The proposed LIPC used local independent projection into the classical classification model, and a novel classification framework was derived. Compared with other coding approaches, the LAE method was more suitable in solving the linear reconstruction weights under the locality constraint. The data distribution in each sub manifold was important for the classification, and we used a softmax model to learn the relationship between the data distribution and reconstruction error norm. We evaluated the proposed method using both synthetic data and public available Diabetic Foot ulcer image data. In both problems, our method outperformed competing methods.

REFERENCES

[1] Praveen Kumar Ramtekkar, Anjana Pandey & Mahesh Kumar Pawar, "Accurate detection of Diabetic Foot ulcer using optimized feature selection based on deep learning techniques" - 2023 Springer

[2] Shubhangi Solanki, Uday Pratap Singh, Siddharth Singh Chouhan, and Sanjeev Jain, "Diabetic Foot Ulcer Detection and Classification Using Intelligence Techniques: An Overview" - 2023 IEEE

[3] Md Ishtyaq Mahmud,Muntasir Mamun, and Ahmed Abdelgawad, "A Deep Analysis of Diabetic Foot Ulcer Detection from MR Images Using Deep Learning Networks" - 2023 MDPI

[4] Aqsa Tahir, Muhammad Asif, Maaz Bin Ahmad, Toqeer Mahmood, Muhammad Adnan Khan, and Mushtaq Ali6, "Diabetic Foot Ulcer Detection using Decision-Based Fusion Empowered with Fuzzy Logic" – 2022 Hindawi

[5] Anjanayya S, V. M. Gayathri, and R. Pitchai,"Diabetic Foot Ulcer Segmentation and Survival Prediction using Multimodal Scans with Deep learning Algorithms" – 2022 IEEE

[6] Yue Zhang, Benxiang Jiang, Jiong Wu, Dongcen Ji, Yilong Liu, Yifan Chen, Ed X. Wu, and Xiaoying Tang, "Deep Learning Initialized and Gradient Enhanced Level-Set Based Segmentation for Diabetic Foot Ulcer From CT Images" – 2020 IEEE

[7] Tao Lei, Risheng Wang, Yuxiao Zhang, Yong Wan, Chang Liu, and Asoke K. Nandi, "DefED-Net: Deformable Encoder-Decoder Network for Diabetic Foot and Diabetic Foot Ulcer Segmentation". – 2022 IEEE

[8] Xin Dong, Yizhao Zhou, Lantian Wang, Jingfeng Peng, Yanbo Lou, and Yiqun Fan, "Diabetic Foot Ulcer Detection Using Hybridized Fully Convolutional Neural Network Based on Deep Learning Framework". – 2020 IEEE

[9] Simona Turco, Thodsawit Tiyarattanachai, Kambez Ebrahimkheil, John Eisenbrey, Aya Kamaya, Massimo Mischi, Senior Member, Andrej Lyshchik, and Ahmed El Kaffas, "Interpretable Machine Learning for Characterization of Focal Diabetic Foot Lesions by Contrast-Enhanced Ultrasound". – 2022 IEEE

[10] Sowjanya M. N,Stafford Michahia, Mahanthesha U, and Nagalakshmi T. S,"Diabetic Foot Ulcer Detection in Chest X - Ray Image". – 20 IEEE

[11] Dr. H S Mohan and Mahanthesha U, "Human action Recognition using STIP Techniques", International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-7, May 2020

[12] J. F. Allen, "Maintaining knowledge about temporal intervals," Commun. ACM, vol. 26, no. 11, pp. 832–843, Nov. 1983.

[13] C. Fernandez, P. Baiget, X. Roca, and J. Gonzalez, "Interpretation of complex situations in a semantic-based surveillance framework," Image Commun., vol. 23, no. 7, pp. 554–569, Aug. 2008.

[14] J. Candamo, M. Shreve, D. B. Goldgof, D. B. Sapper, and R. Kasturi, "Understanding transit scenes: A survey on human behavior-recognition algorithms," IEEE Trans. Intell. Transp. Syst., vol. 11, no. 1, pp. 206–224, Mar. 2010.

[15] Y. Changjiang, R. Duraiswami, and L. Davis, "Fast multiple object tracking via a hierarchical particle filter," in Proc. 10th IEEE ICCV, 2005, vol. 1, pp. 212–219.

[16] A. Loza, W. Fanglin, Y. Jie, and L. Mihaylova, "Video object tracking with differential Structural SIMilarity index," in Proc. IEEE ICASSP, 2011, pp. 1405–1408.

[17] D. Comaniciu, V. Ramesh, and P. Meer, "Kernel-based object tracking," IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 5, pp. 564–577, May 2003.

[18] V. Papadourakis and A. Argyros, "Multiple objects tracking in the presence of long-term occlusions," Comput. Vis. Image Underst., vol. 114, no. 7, pp. 835–846, Jul. 2010.

[19] Mahanthesh U, Dr. H S Mohana "Identification of Human Facial Expression Signal Classification Using Spatial Temporal Algorithm" International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE) Vol 2, Issue 5, May 2016

[20] NikiEfthymiou, Petros Koutras, Panagiotis, Paraskevas, Filntisis, Gerasimos Potamianos, Petros Maragos "Multi-View Fusion for Action Recognition in Child-Robot Interaction": 978-1-4799-7061-2/18/$31.00 ©2018 IEEE.

[21] Nweke Henry Friday, Ghulam Mujtaba, Mohammed Ali Al-garadi, Uzoma Rita Alo, analysed "Deep Learning Fusion Conceptual Frameworks for Complex Human Activity Recognition Using Mobile and Wearable Sensors": 978-1-5386-1370-2/18/$31.00 ©2018 IEEE.

[22] Van-Minh Khong, Thanh-Hai Tran, "Improving human action recognition with two-stream 3D convolutional neural network", 978-1-5386-4180-4/18/$31.00 ©2018 IEEE.

[23] Nour El Din Elmadany , Student Member, IEEE, Yifeng He, Member, IEEE, and Ling Guan, Fellow, IEEE ,"Information Fusion for Human Action Recognition via Biset /Multiset Globality Locality Preserving Canonical Correlation Analysis" IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 27, NO. 11, NOVEMBER 2018.

[24] Pavithra S, Mahanthesh U, Stafford Michahial, Dr. M Shivakumar, "Human Motion Detection and Tracking for Real-Time Security System", International Journal of Advanced Research in Computer and Communication Engineering ISO 3297:2007 Certified Vol. 5, Issue 12, December 2016.

[25] Lalitha. K, Deepika T V, Sowjanya M N, Stafford Michahial, "Human Identification Based On Iris Recognition Using Support Vector Machines", International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE) Vol 2, Issue 5, May 2016

[26] RoozbehJafari, Nasser Kehtarnavaz "A survey of depth and inertial sensor fusion for human action recognition", https://link.springer.com/article/10.1007/s11042-015-3177-1, 07/12/2018.

[27] Rawya Al-Akam and Dietrich Paulus, "Local Feature Extraction from RGB and Depth Videos for Human Action Recognition", International Journal of Machine Learning and Computing, Vol. 8, No. 3, June 2018

[28] V. D. Ambeth Kumar, V. D. Ashok Kumar, S. Malathi, K. Vengatesan and M. Ramakrishnan, "Facial Recognition System for Suspect Identification Using a Surveillance Camera", ISSN 1054-6618, Pattern Recognition and Image Analysis, 2018, Vol. 28, No. 3, pp. 410–420. © Pleiades Publishing, Ltd., 2018.