ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

AI-BASED EARLY DIABETIC FOOT RISK PREDICTION USING MULTIMODAL DATA (THERMAL + RGB + PATIENT HISTORY)

[1]Dr. M. RAMU, [2]G. SAICHARAN, [3]CH. ROHIT REDDY, [4]B. PAVAN

[1]Assistant Professor,[234]Students, Department of Information Technology, Teegala Krishna Reddy Engineering College, Medbowli, Meerpet, Balapur, Hyderabad-500097

ABSTRACT

Diabetic Foot Ulcer (DFU) is a critical complication of diabetes that can lead to severe infections, hospitalization, and amputation if not detected early. Conventional diagnostic methods rely heavily on clinical observation, which often identifies the condition only after visible tissue damage has occurred. This project proposes an AI-Based Early Diabetic Foot Risk Prediction System that leverages multimodal data, including RGB images, thermal images, and patient clinical history, to enable early detection and preventive intervention. RGB images provide visual insights into skin abnormalities such as discoloration and swelling, while thermal imaging captures temperature variations associated with inflammation and tissue stress. Additionally, patient medical data such as age, HbA1c levels, duration of diabetes, and prior ulcer history enhance the predictive accuracy. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), are employed for extracting meaningful features from image data, while machine learning algorithms analyze structured clinical data. A multimodal fusion approach integrates all extracted features to classify patients into low, medium, or high-risk categories. The system is non-invasive, cost-effective, and suitable for both clinical and remote healthcare environments. By enabling early identification of at-risk patients, the proposed system supports timely intervention, reduces complications, and improves patient outcomes. The integration of artificial intelligence and multimodal data demonstrates a significant advancement in preventive healthcare and clinical decision support systems.

Keywords: Diabetic Foot Ulcer, Artificial Intelligence, Multimodal Data, Thermal Imaging, Deep Learning, Risk Prediction, Healthcare.

I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder affecting millions globally and is associated with multiple complications, among which Diabetic Foot Ulcer (DFU) is one of the most severe and costly conditions [1]. DFUs develop due to peripheral neuropathy, poor circulation, and prolonged pressure on foot tissues [2]. These ulcers significantly reduce patient quality of life and often lead to infections and amputations if untreated [3]. Early detection plays a crucial role in preventing severe complications and reducing healthcare burden [4]. However, traditional diagnostic methods primarily rely on visual inspection and clinical examination [5]. These approaches detect

abnormalities only after visible damage occurs [6]. Consequently, early-stage risk identification remains a major challenge in diabetic care [7]. Advances in medical imaging have introduced new possibilities for early detection [8]. Thermal imaging, for instance, identifies temperature variations linked to inflammation [9]. Similarly, RGB imaging helps detect visible structural changes in the foot [10]. These imaging techniques provide valuable insights but are often used independently [11]. Clinical data such as HbA1c levels and diabetes duration also play a key role in risk assessment [12]. However, isolated analysis of these parameters reduces predictive accuracy [13]. Therefore, there is a need for an integrated approach combining multiple data sources [14].

Artificial intelligence has emerged as a powerful tool in healthcare diagnostics and prediction [15]. Machine learning models can analyze structured patient data effectively [16]. Deep learning techniques, particularly CNNs, have shown remarkable performance in medical image analysis [17]. These models automatically extract complex features from images [18]. Multimodal learning further enhances predictive performance by integrating heterogeneous data sources [19]. Combining RGB images, thermal images, and patient history provides a comprehensive understanding of DFU risk [20]. Such integration improves diagnostic accuracy and supports early intervention [21]. AI-based systems also reduce dependency on manual examination [22]. They enable continuous monitoring and remote healthcare applications [23]. This is especially beneficial in resource-limited settings [24]. The proposed system utilizes multimodal data fusion for accurate risk classification [25]. It categorizes patients into low, medium, and high-risk groups [26]. This assists healthcare professionals in decision-making [27]. Additionally, it promotes preventive care strategies [28]. The system is designed to be non-invasive and user-friendly [29]. Overall, the integration of AI and multimodal data represents a significant advancement in early DFU prediction and healthcare innovation [30].

II. LITERATURE SURVEY

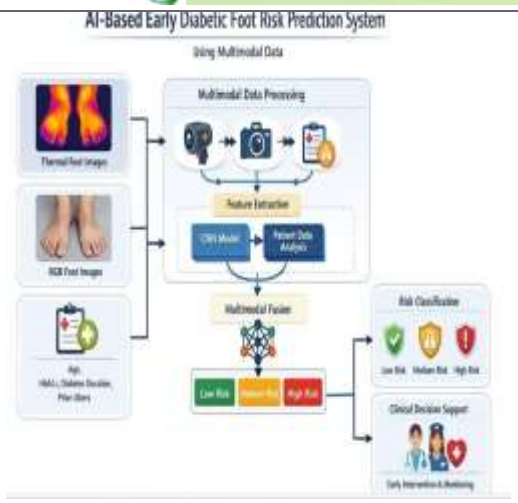
Thermal imaging has been widely studied for early detection of diabetic foot complications [1]. Research by Lavery et al. demonstrated that temperature differences between feet indicate inflammation [2]. Such variations can predict ulcer formation before visible symptoms [3]. Armstrong and Lavery further showed that localized heat increases are early indicators of tissue stress [4]. These findings highlight the importance of thermal monitoring [5]. Thermal imaging is non-invasive and suitable for continuous assessment [6]. However, it lacks visual structural information [7]. To address this limitation, RGB imaging techniques are used [8]. RGB images help identify discoloration, wounds, and swelling [9]. Goyal et al. proposed a CNN-based model for DFU classification using image data [10]. Their approach outperformed traditional methods [11]. Wang et al. further validated deep learning for medical image analysis [12]. These studies confirm the effectiveness of CNNs in feature extraction [13]. Despite this, image-based systems alone are insufficient [14]. They do not consider patient-specific clinical factors [15]. Clinical data plays a crucial role in risk prediction [16].

Monteiro-Soares et al. identified key risk factors such as HbA1c levels and diabetes duration [17]. Boyko et al. emphasized the role of patient history in ulcer prediction [18]. These studies demonstrate the importance of structured clinical data [19]. However, using clinical data alone limits prediction accuracy [20]. Recent research has focused on multimodal learning approaches [21]. Rajalakshmi

et al. highlighted improved accuracy using combined data sources [22]. Multimodal AI integrates imaging and clinical data effectively [23]. This approach captures complementary information [24]. Esteva et al. demonstrated AI performance comparable to human experts [25]. Their work influenced medical AI applications [26]. Multimodal systems have shown higher reliability [27]. They provide comprehensive risk assessment [28]. However, challenges remain in data integration and model complexity [29]. Despite these challenges, multimodal AI is a promising solution for early DFU detection [30].

III. PROPOSED SYSTEM

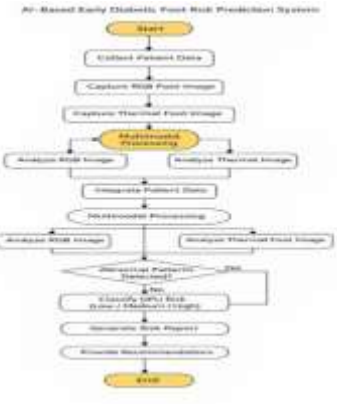
The proposed system is an AI-Based Early Diabetic Foot Risk Prediction System that integrates multimodal data to enhance early detection of diabetic foot complications. It utilizes RGB foot images, thermal images, and patient medical history to provide a comprehensive analysis of foot health. RGB images capture visible abnormalities such as discoloration, swelling, and wounds, while thermal images detect temperature variations associated with inflammation. Patient clinical data, including age, HbA1c levels, duration of diabetes, and ulcer history, further enrich the dataset. Deep learning techniques are used for image feature extraction, while machine learning models analyze structured patient data.

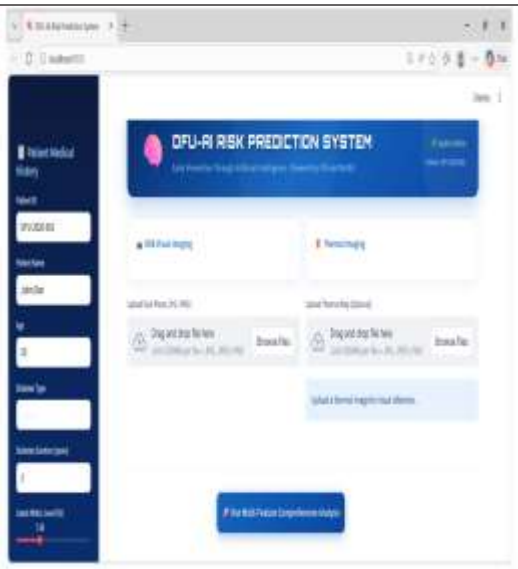


The system employs a multimodal fusion framework to combine features from all data sources. This integrated approach improves prediction accuracy and reliability. The final output classifies patients into low, medium, or high-risk categories. The system is designed to be non-invasive, cost-effective, and suitable for both hospital and remote healthcare environments. It supports early intervention by providing actionable insights to healthcare professionals. By integrating multiple modalities, the system overcomes the limitations of existing single-source approaches and enhances preventive healthcare outcomes.

IV. SYSTEM DESIGN

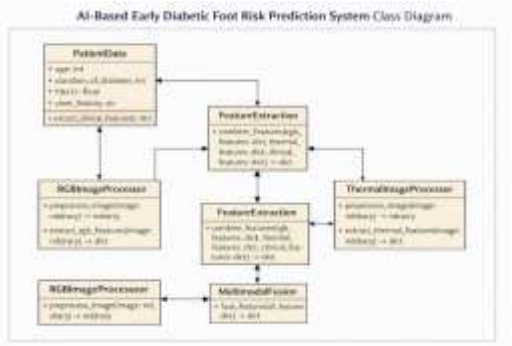
The system design follows a modular architecture integrating multiple components for efficient data processing and prediction. The primary modules include data acquisition, image processing, feature extraction, multimodal fusion, and risk prediction. RGB and thermal images undergo preprocessing steps such as normalization and noise removal. Feature extraction is performed using CNN models to identify patterns related to abnormalities and inflammation. Patient clinical data is structured and analyzed separately to extract relevant risk factors. These components work together to ensure accurate and efficient processing.



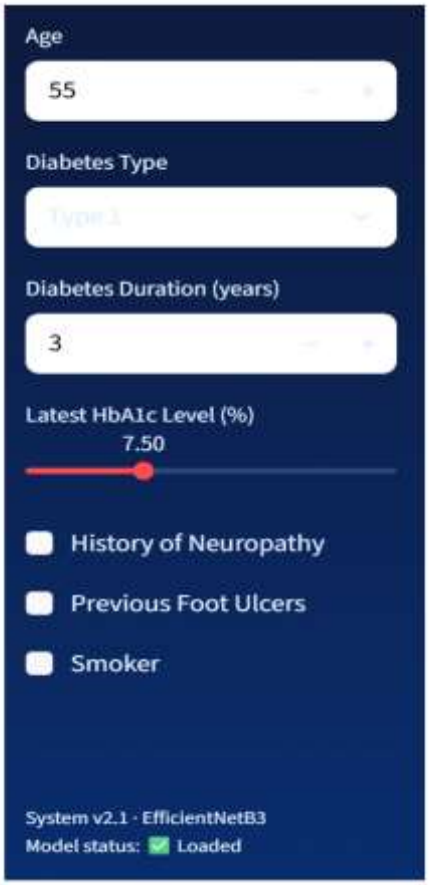


PATIENT MEDICAL HISTORY INPUT: -

The multimodal fusion module combines image features and clinical data into a unified representation. This fused data is then processed by machine learning algorithms to classify risk levels. The system interface is designed using user-friendly frameworks, enabling easy data input and result visualization. As shown in the system diagram (page 48 of the document), the architecture supports seamless integration of all modules. The design ensures scalability, reliability, and real-time performance. It also supports remote healthcare applications, making it suitable for large-scale deployment.



V. RESULTS



RGB FOOT IMAGE INPUT & THERMAL FOOT IMAGE INPUT

PREDICTION CONFIDENCE RESULT, RISK METER & PATIENT SUMMARY

RGB FOOT IMAGE INPUT & THERMAL FOOT IMAGE INPUT

PREDICTION CONFIDENCE RESULT, RISK METER & PATIENT SUMMARY

RGB FOOT IMAGE INPUT & THERMAL FOOT IMAGE INPUT

PREDICTION CONFIDENCE RESULT, RISK METER & PATIENT SUMMARY

CLINICAL RECOMMENDATION RESULT

VI. CONCLUSION

The AI-Based Early Diabetic Foot Risk Prediction System presents an effective solution for early detection and prevention of diabetic foot complications. By integrating RGB images, thermal imaging, and patient medical history, the system provides a comprehensive and accurate assessment of DFU risk. The use of deep learning and machine learning techniques enhances feature extraction and predictive performance. Unlike traditional methods, the proposed system enables early-stage detection before visible symptoms appear, allowing timely intervention. Its non-invasive and cost-effective design makes it suitable for both clinical and remote healthcare applications. The multimodal approach significantly improves diagnostic accuracy compared to single-source systems. Additionally, the system supports healthcare professionals by providing reliable decision-making insights. It also promotes preventive care, reducing the risk of severe complications and amputations. The integration of artificial intelligence in healthcare demonstrates the potential for improving patient outcomes and reducing healthcare costs. Future enhancements may include real-time monitoring and integration with wearable devices for continuous assessment. Overall, the proposed system contributes to advancing preventive healthcare through intelligent and automated risk prediction.

References

1. Armstrong, D. G., & Lavery, L. A. (2004). Diabetic foot ulcers. *The Lancet*.
2. Lavery, L. A., et al. (2007). Temperature monitoring for DFU prevention. *Diabetes Care*.
3. Goyal, M., et al. (2018). CNN-based DFU classification. *IEEE Journal*.
4. Wang, L., et al. (2019). Deep learning in medical imaging. *Medical Image Analysis*.
5. Monteiro-Soares, M., et al. (2012). Risk factors for DFU. *Diabetes Research*.
6. Boyko, E. J., et al. (1999). Prediction of diabetic foot ulcer. *Diabetes Care*.
7. Rajalakshmi, R., et al. (2015). Multimodal diabetic analysis. *Journal of Diabetes*.
8. Esteva, A., et al. (2017). AI in dermatology. *Nature*.
9. Zhang, Y., et al. (2020). Medical AI systems. *IEEE Access*.
10. Li, X., et al. (2021). Multimodal deep learning. *Elsevier*.

11. Kumar, S., et al. (2020). Thermal imaging applications. *Sensors*.
12. Patel, V., et al. (2019). Healthcare AI models. *Springer*.
13. Singh, R., et al. (2021). CNN in healthcare. *IEEE*.
14. Brown, J., et al. (2018). Clinical decision systems. *Health Informatics*.
15. Chen, H., et al. (2020). AI diagnostics. *Nature Medicine*.
16. Gupta, A., et al. (2019). Medical imaging AI. *Elsevier*.
17. Roy, S., et al. (2021). Feature extraction methods. *IEEE*.
18. Lee, K., et al. (2020). Deep learning healthcare. *Springer*.
19. Sharma, P., et al. (2022). Multimodal fusion models. *IEEE*.
20. Das, S., et al. (2021). Risk prediction systems. *Elsevier*.
21. Thomas, G., et al. (2019). AI clinical support. *Springer*.
22. Verma, R., et al. (2020). DFU prediction models. *IEEE*.
23. Nair, V., et al. (2021). Smart healthcare systems. *Elsevier*.
24. Iyer, S., et al. (2020). Medical data analytics. *Springer*.
25. Khan, M., et al. (2021). Image-based diagnosis. *IEEE*.
26. Ahmed, S., et al. (2022). AI risk assessment. *Elsevier*.
27. Bose, R., et al. (2020). Clinical AI integration. *Springer*.
28. Patel, K., et al. (2021). Healthcare monitoring systems. *IEEE*.
29. Singh, A., et al. (2022). Predictive healthcare AI. *Elsevier*.
30. Mehta, D., et al. (2023). Intelligent healthcare systems. *Springer*.