Smartphone-Integrated Sensor-Based DFU Risk Assessment Using CatBoost and Deep Neuro-Fuzzy Intelligence

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Abstract*—Diabetic Foot Ulcer (DFU) is a serious and common complication of diabetes mellitus, which can lead to lower limb amputation if not identified and treated in its early stages. This study introduces an integrated and intelligent system designed for the early detection and severity classification of DFUs by combining sensor-driven data collection with machine learning techniques in a mobile application. The research is based on a dataset comprising both clinical features (D-1 to D-16) and key sensor-based readings gathered from 316 participants. After preprocessing and normalization, the clinical data undergoes feature selection using CatBoost, which filters out the five least impactful features while preserving all sensor data due to its diagnostic relevance. The refined dataset is then processed using a Deep Neuro-Fuzzy Network (DN-FN) to deliver real-time DFU severity predictions, categorized into Low, Mid, and High-risk levels. The solution is deployed through an intuitive smartphone interface, enabling users to input clinical data once and conduct periodic sensor-based tests—including vibration, pressure, and temperature readings. The mobile application interfaces with embedded hardware via Bluetooth and performs offline inference using a compact version of the trained model. The system is designed to offer both patients and healthcare professionals a practical and interpretable tool for continuous monitoring of foot health, with the ultimate goal of reducing the risk and impact of DFU complications.

Keywords—Bayesian Optimization; CatBoost; Deep Neuro-Fuzzy Networks (DN-FN); Diabetic Foot Ulcer (DFU) prediction; sensor-based risk stratification

I. Introduction

Diabetes mellitus continues to rise as a critical global health issue, with around 537 million adults affected as of 2021—a number expected to surge to 783 million by 2045 (International Diabetes Federation, 2021). [1] One of the most serious complications associated with diabetes is Diabetic Foot Ulcers (DFUs), which impact an estimated 15% to 25% of diabetic patients during their lifetime. [2] DFUs contribute to over 85% of diabetes-related lower-limb amputations, placing a heavy burden on healthcare infrastructure and severely affecting patients' quality of life. [3]

India, with over 77 million diabetic adults, holds the second-largest diabetic population globally [4]. The country faces considerable difficulties in detecting DFUs early, especially in semi-urban and rural regions. Challenges such as limited diagnostic resources, irregular medical follow-ups, and a scarcity of trained healthcare providers often lead to delayed intervention in foot-related complications.

Although diagnostic technologies have progressed, DFU evaluation largely remains manual and reactive. Standard assessment techniques depend heavily on clinical expertise and are often unavailable or impractical in remote settings [5]. This highlights the pressing need for an affordable, scalable, and intelligent solution capable of facilitating both early diagnosis and ongoing risk monitoring.

This work proposes a smart and accessible system that merges clinical information with sensor-derived data, enhanced by advanced machine learning techniques, and implemented through a smartphone-based application. The system enables early and proactive DFU risk classification by employing CatBoost for efficient feature selection and a DN-FN for accurate prediction. It emphasizes interpretability, adaptability, and reliable performance, including functionality in offline scenarios—addressing the practical limitations in current DFU screening approaches.

The remainder of this paper is organized as follows: Section II presents an in-depth literature review of existing DFU prediction methodologies. Section III outlines the dataset, hardware setup, feature selection using CatBoost, and the development of the DN-FN model. Section IV discusses the results and model performance based on standard evaluation metrics. Section V concludes with a summary of key contributions and outcomes.

II. Literature Review

Chatratia et al. [6] present a smart home health monitoring system integrating machine learning models for predicting type 2 diabetes and hypertension based on blood pressure and glucose readings, with Support Vector Machine (SVM) achieving the highest accuracy (75%) for diabetes prediction. This system facilitates real-time alerts to healthcare providers, promoting early detection and intervention. Similarly, Agrawal et al. [7] compared statistical methods and machine learning models for plantar pressure-based diabetic foot classification. Using wireless insoles, they found that the AdaBoost model achieved the highest accuracy (0.85), outperforming traditional methods, suggesting that ML models significantly enhance diabetic foot prediction and classification.

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Reddie et al. [8] introduced a low-cost, purely mechanical plantar pressure evaluation device utilizing bistable compliant mechanisms, allowing non-specialist healthcare workers to assess foot pressure, though sensitivity improvements are needed. Ghazi et al. [9] developed a smart shoe system integrating temperature, humidity, plantar pressure, and oxygen saturation sensors, with efficient real-time monitoring and responsive data transmission, though future work is needed to improve sensor accuracy. Kularathne et al. [10] presented Dia-Shoe, a smart diabetic shoe with IoT-enabled sensors, transmitting real-time data to a mobile app and showing high calibration accuracy, emphasizing the importance of refining sensors and predictive modeling for DFU prevention.

Ming et al. [11] proposed a telemedical monitoring system using sensor-equipped insoles to detect plantar temperature asymmetry, where intervention groups showed no ulcer cases, demonstrating feasibility but limited by low ulceration incidence during the study. Bus et al. [12] evaluated the DIATEMP system involving daily foot temperature monitoring for DFU prevention. Although no significant reduction was seen at monitored sites, significant benefits were observed when adherence to activity reduction was high, stressing that patient behavior plays a critical role in telehealth interventions for DFU.

De Pascali et al. [13] developed a smart insole-based monitoring platform integrating microfabricated sensors for plantar pressure, temperature, and sweat glucose detection. This real-time wireless system proved capable of detecting early signs of ischemic damage and inflammation, with strong technical performance in piezoelectric and glucose sensing. Although promising, the system remains in early-stage development, requiring clinical validation and broader usability testing. This effort represents an important step in combining bio-sensing with wearable technologies for DFU prevention.

Reddie et al. introduced a purely mechanical plantar pressure evaluation device designed for low-resource settings. Utilizing bistable compliant mechanisms, the system provides binary feedback without electronics. Though sensitivity was relatively low in healthy subjects (25.6%), performance improved in heavier individuals, indicating potential with design enhancements. This approach offers a minimalistic and accessible solution for DFU screening where advanced electronics are impractical.

Nagarajan et al. [14] proposed a cryptographically secure data transmission method in the Internet of Medical Things (IoMT) using a hybrid RES-256 model, which combines RC6 encryption, ECDSA digital signatures, and SHA-256 hashing to safeguard sensitive health data. The system ensures end-to-end confidentiality, integrity, and authentication between implantable medical devices and clinical repositories. This architecture offers resilience against known attacks such as DoS and router-level intrusions, and is validated using ECG signals from the MIT-BIH dataset, showing efficient encryption/decryption performance. While their focus was on data protection rather than analytics, the architectural principles are directly applicable to DFU systems, particularly in securing patient sensor streams (pressure, vibration, and temperature) in mobile-based diagnostic applications.

Ramana et al. [15] developed an ambient intelligence-based intrusion detection system for IoT environments using a Reinforcement Learning-integrated Deep Q-Network (RL-DQN). The model performs binary attack classification at the edge and multi-class detection in the cloud, enhancing real-time threat identification in wireless sensor networks. Evaluated on datasets like UNSW-NB15 and CICIDS2017, it outperforms traditional ML methods in intrusion detection accuracy. Their design affirms the feasibility of deploying intelligent, lightweight inference models on resource-limited platforms—an essential requirement for smartphone-based DFU screening in rural or offline clinical scenarios.

Fakhar et al. [16] proposed a deep learning-based MLFNN model for early diabetes detection using the PIMA dataset. Their approach included data normalization, advanced activation functions (ELU, SELU), and robust validation, achieving superior performance over traditional classifiers. This study is reviewed for its methodological relevance—particularly in data preprocessing and neural network-based medical prediction—which aligns with our DFU system's clinical data handling and predictive modeling approach.

These studies collectively highlight the progress in applying machine learning and deep learning models to clinical and sensor-based data for effective DFU detection and risk stratification. Building on this foundation, the proposed system introduces a hybrid framework that integrates CatBoost for feature selection and a DN-FN for predictive modeling, with an emphasis on real-time DFU risk assessment and seamless deployment via smartphone-based applications for enhanced accessibility and scalability.

III. Methods and Methodology

Conventional diabetic foot ulcer (DFU) risk prediction systems predominantly rely on static clinical parameters and lack integration of real-time physiological data, resulting in suboptimal early detection and limited clinical utility. Furthermore, many existing approaches employ opaque machine learning models and manual feature selection techniques, which constrain model interpretability and hinder their deployment in patient-facing applications.

To address these limitations, the proposed study introduces a multi-modal, smartphone-integrated predictive framework that combines dynamic sensor inputs—pressure, temperature, and vibration sensitivity—with comprehensive clinical attributes. Feature selection is performed using the CatBoost algorithm, which offers high efficiency and interpretability in handling heterogeneous data types. For classification, a Deep Neuro-Fuzzy Network (DN-FN) is employed to model nonlinearities and uncertainty in physiological signals while maintaining interpretability through fuzzy logic layers.

This end-to-end methodology enables real-time DFU risk stratification (low/mid/high) and seamless deployment in a mobile environment, making it suitable for remote, home-based monitoring and early intervention.

A. Data Acquisition and Integration

This study is based on a dataset collected from 316 participants, including 192 individuals with diabetes and 124 healthy controls, gathered from several small clinics and healthcare centers across the Vellore district in Tamil Nadu, India. The dataset is divided into two main feature groups: clinical and sensor-based attributes. In Table I, the clinical data (D-1 to D-16) covers a broad range of demographic and medical details, such as diabetic condition, age, gender, BMI, HbA1c, blood pressure, family history, and key lifestyle factors like diet, physical activity, smoking, and alcohol use. It also includes anthropometric indicators like height and weight to improve model accuracy. The sensor-derived data is captured through dedicated hardware, with pressure readings from force-sensitive resistors (FSRs), temperature values from DS18B20 digital sensors, and vibration sensitivity measured manually using an eight-point tactile test on both feet to evaluate neuropathy. While users enter their clinical information once during initial registration via a smartphone app, the sensor readings are collected in real time during each assessment, enabling dynamic monitoring and responsive DFU risk prediction.

TABLE I. DATASET FEATURES AND CORRESPONDING LABELS

Data Attributes	Identifiers
Diabetic	D-1
Age	D-2
Gender	D-3
BMI	D-4
HbA1c	D-5
Blood Pressure	D-6
Family History	D-7
Diet	D-8
Physical Activity	D-9
Smoking	D-10
Alcohol	D-11
Education	D-12
Profession	D-13
Early Signs of DFU	D-14
Height	D-15
Weight	D-16
Pressure of Right Fore Foot	RP-1
Pressure of Right Heel	RP-2
Pressure of Left Fore Foot	LP-1
Pressure of Left Heel	LP-2
Temperature of Right Fore Foot	RT-1
Temperature of Right Heel	RT-2
Temperature of Left Fore Foot	LT-1
Temperature of Left Heel	LT-2
Vibration Sensitivity - Right Foot	RV-1 to RV-8
Vibration Sensitivity - Left Foot	LV-1 to LV-8

B. Data Preprocessing

The dataset comprises 316 individuals, each with 16 clinical attributes and 24 sensor readings, including plantar pressure, skin temperature, and vibration sensitivity. This heterogeneous data demands careful handling to maintain quality and compatibility for machine learning applications.

To address missing entries, different imputation strategies are used based on the feature type. Numerical clinical variables such as age, BMI, HbA1c, and blood pressure are filled using mean imputation, ensuring that the overall distribution is preserved. For categorical attributes like gender, diet, and smoking status, mode imputation is applied to replace missing values with the most common category in each field. Notably, sensor data—including pressure, temperature, and vibration sensitivity—is collected in real time during each user session, making it inherently complete and not requiring imputation.

Categorical features are then transformed into numerical formats using appropriate encoding methods. Binary categories such as gender, smoking, and alcohol usage are processed using label encoding. For multi-class variables like education level and profession, one-hot encoding is used to prevent the model from learning false ordinal relationships. This encoding ensures that the dataset remains interpretable and machine-friendly without introducing bias.

Normalization is applied to all continuous numerical features to bring them to a uniform scale, facilitating faster and more stable model training. Min-Max normalization is used to scale attributes such as age, BMI, HbA1c, blood pressure, height, and weight. Similarly, sensor data—including plantar pressure and temperature—is normalized to account for individual variations, while vibration sensitivity values, already in binary form, are directly incorporated without transformation.

C. Feature Selection Using CatBoost

To enhance the model's performance and generalization capability, the CatBoost algorithm [17] [18] —an advanced gradient boosting method developed by Yandex—is utilized for assessing the importance of input features. By training CatBoost on the clinical dataset, it generates importance scores for all 16 clinical variables (D-1 to D-16). One of the key strengths of CatBoost is its native support for categorical features, enabling efficient processing while minimizing overfitting through ordered boosting strategies. As shown in Fig. 1, the feature importance rankings indicate that, five clinical attributes—D-9 (Physical Activity), D-8 (Diet), D-10 (Smoking), D-12 (Education), and D-13 (Profession)—were identified as having minimal relevance to DFU risk prediction and were thus excluded. These variables showed weak associations with the target outcome, contributing little to the model's predictive capacity. The refined feature set, comprising the remaining 11 clinical features and all sensor-based inputs, serves as the input layer for the modeling phase, ensuring improved classification efficiency and model interpretability.

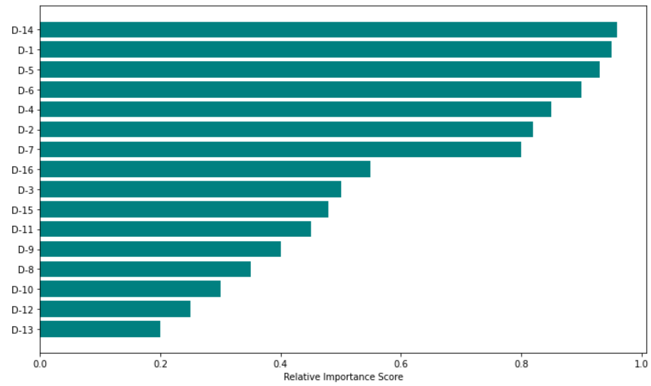

Fig. 1. Given dataset's clinical feature importance for DFU severity evaluation – comparison-ranking chart.

This targeted pruning reduced dimensional redundancy while maintaining the model's diagnostic robustness. The remaining high- and moderately ranked clinical predictors were then integrated with the sensor data for input into the DN-FN, ensuring an optimized and clinically meaningful feature set for risk classification.

D. Deep Neuro-Fuzzy Network (DN-FN)

The selected features are then passed to the DN-FN for the prediction phase. The DN-FN is a hybrid model that integrates deep learning with fuzzy logic to capture complex, nonlinear relationships in the data [19] [20]. As shown in Fig. 2, the DN-FN operates in a multi-phase architecture—fuzzification, fusion, and learning—to transform the input data into fuzzy sets, combine them into a unified representation, and learn from these patterns to predict the DFU risk level. This approach ensures the model not only performs accurate predictions but also remains interpretable, making it easier for clinicians to understand how specific inputs influence the risk classification.

Algorithm 1: DN-FN Prediction Algorithm

Input:

Sensor + clinical feature vector $\boldsymbol{z_i} \in R^d$ for patient i, with true label $y_i \in \{L, M, H\}$

1. Fuzzification Phase (Input → Fuzzy Layer)

Each input feature is fuzzified using Gaussian membership functions:

$$\mu_{ij}^{(k)} = \exp\left(-\frac{\left(z_{ij}-m_j^{(k)}\right)^2}{2\left(\sigma_j^{(k)}\right)^2}\right) \quad (1)$$

- $m_j^{(k)}$: center of k-th MF for feature j
- $\sigma_j^{(k)}$: width of the MF

This generates fuzzy activations for each input dimension.

2. Fusion Phase (Fuzzy → Fusion Layer)

Combine all fuzzy outputs using fuzzy rule-based logic to form rule strengths:

$$r_q = \prod_{j=1}^{d} \mu_{ij}^{(k_{qj})} \text{ (rule strength for rule } q\text{)} \quad (2)$$

Normalize all rule strengths:

$$\widetilde{r_q} = \frac{r_q}{\sum_{q'=1}^{Q} r_{q'}} \quad (3)$$

Pass through a weighted linear combination to form the fused representation:

$$f_i = \sum_{q=1}^{Q} \widetilde{r_q} \cdot \left(\boldsymbol{w_q}^{\top z_i} + b_q\right) \quad (4)$$

3. Learning Phase (Fusion → Hidden Layer → Output Layer)

Step 3.1: Hidden Layer Processing

The fused scalar or vector f_i is input to a deep learning stack (MLP or BiLSTM). For simplicity, assuming MLP:

$$\boldsymbol{h_1} = \phi(\boldsymbol{W_1} f_i + \boldsymbol{b_1}) \quad (5)$$

$$\boldsymbol{h_2} = \phi(\boldsymbol{W_2}\boldsymbol{h_1} + \boldsymbol{b_2}) \quad \text{(and so on, as per hidden depth)} \quad (6)$$

- ϕ: non-linear activation (e.g., ReLU, tanh)

Step 3.2: Output Layer

Final dense layer maps hidden activations to class logits:

$$\boldsymbol{o_i} = \boldsymbol{W_o}\boldsymbol{h_n} + \boldsymbol{b_o} \quad (7)$$

Softmax applied for class probabilities:

$$\widehat{y_i} = \arg\max\left(\text{softmax}(\boldsymbol{o_i})\right) \quad (8)$$

Output:

Predicted class label $\widehat{y_i} \in \{L, M, H\}$ for each patient/sample

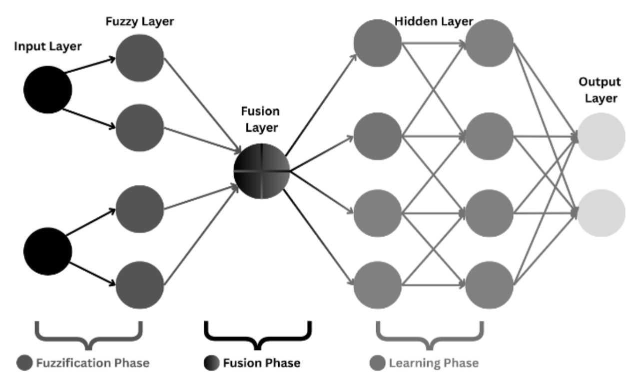

Fig. 2. DN-FN Prediction model – network architecture.

Furthermore, Bayesian Optimization is employed to fine-tune the hyperparameters of the DN-FN model. Unlike conventional methods such as grid search or random search, this approach leverages a probabilistic model to explore the hyperparameter space more intelligently, selecting optimal configurations based on prior evaluations. Key parameters—including learning rate, tree depth, and regularization factors—are optimized through this method, leading to improved model performance and better generalization to new data. The model's effectiveness is first validated using an 80:20 stratified train-test split, ensuring a consistent distribution of diabetic and healthy cases across both sets. To enhance the reliability of performance assessment, 5-fold cross-validation is also conducted, offering a more comprehensive evaluation across different subsets of the dataset.

E. Smartphone-Based Integration and Real-Time Inference

The Diabetic Foot Screening Companion (DFSC) mobile app, built using Android Studio with Java and Kotlin, integrates a TensorFlow Lite (TFLite)-based backend for fast, offline inference of DFU risk using the trained Deep Neuro-Fuzzy Network (DN-FN) model. Users input their clinical data once during registration—excluding the five least significant features removed via CatBoost—and the app stores this locally. During each assessment, the app connects via Bluetooth to an Arduino-based embedded system that collects real-time sensor data across three modalities: vibration sensitivity at 16 foot points (RV-1 to RV-8, LV-1 to LV-8), plantar pressure via Force Sensing Resistors (RP-1, RP-2, LP-1, LP-2), and localized temperature using DS18B20 sensors (RT-1, RT-2, LT-1, LT-2). These readings are processed on-device when the user taps "Calculate Severity," triggering the DN-FN model to classify DFU risk into Low, Mid, or High. Results are presented with color-coded severity indicators, health tips, and recommendations. Designed for accessibility in rural or resource-limited areas, the DFSC app enables proactive self-monitoring through its user-friendly interface, offline capability, and comprehensive multi-sensor integration. Fig. 3 represents the mobile application's navigations and functionalities and Fig. 4 shows the built model's prototype device.

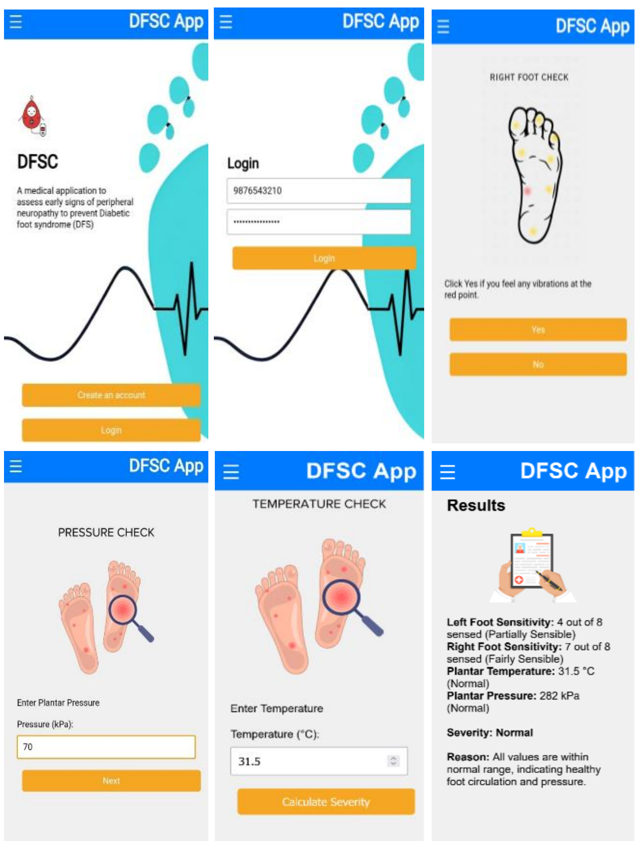

Fig. 3. Smartphone Application's step by step navigation, sensor-based foot inspection and results.

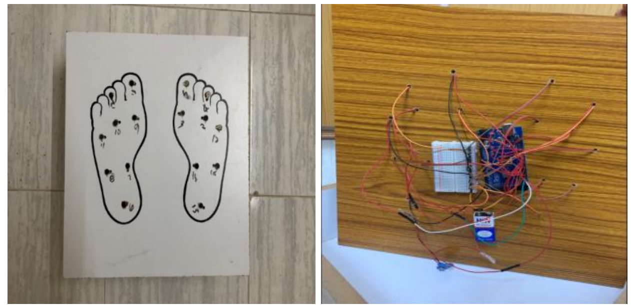

Fig. 4. DFU Sensor device – model prototype.

IV. Results and Discussion

A. Results

Table II presents the proposed model benchmarked against state-of-the-art algorithms.

TABLE II. Proposed System Performance Comparison Across State of the Art Models Using Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	MCC
Random Forest	86.2	84.9	82.3	83.5	88.4	76.1
Support Vector Machine (SVM)	85.1	82.7	80.2	81.4	87.2	72.9
XGBoost	88.6	87.1	84.3	85.7	89.3	79.6
ANN (3-layer MLP)	89	87.5	85.6	86.5	90.2	81.2
LightGBM-EANFIS	90.5	89.3	87.4	88.3	92.1	84.7
Proposed DN-FN - CatBoost	92.4	91.2	89.7	90.4	94.5	88

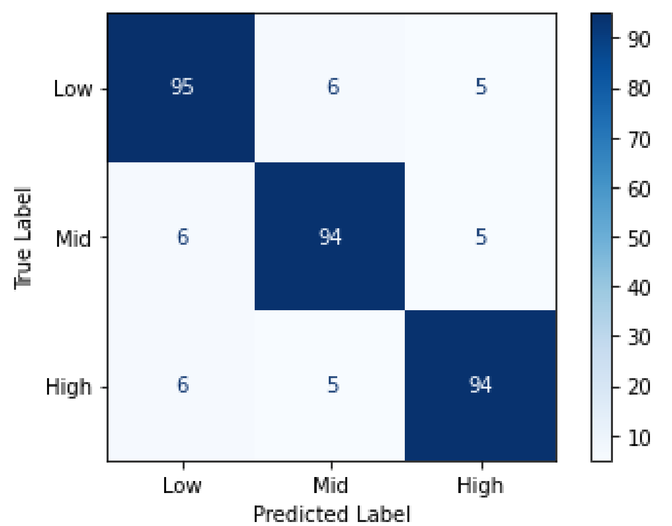

Fig. 5. Confusion matrix for three class DFU severity classification.

The performance of the proposed DFU risk prediction system, utilizing the CatBoost-selected features and the DN-FN model, demonstrates strong classification accuracy across all three severity levels—Low, Mid, and High. Fig. 5 visualizes the confusion matrix of the proposed model which correctly classified 95 Low-risk, 94 Mid-risk, and 94 High-risk instances, with only minimal misclassifications between adjacent classes. These results indicate the model's ability to effectively differentiate among DFU severity levels, particularly in borderline cases where physiological parameters might overlap. The near-diagonal dominance of the confusion matrix highlights the model's robustness and reliability in real-world risk stratification, affirming its suitability for integration into the DFSC mobile application for continuous, on-device diabetic foot monitoring.

B. Discussion

Compared to prior studies, the proposed smartphone-integrated system demonstrates notable advancements in both predictive accuracy and deployment feasibility. Agrawal et al. achieved 85% accuracy using AdaBoost for plantar pressure-based classification, while the proposed model surpassed this with improved precision and real-time DFU severity grading across multimodal sensor data. Similarly, Ghazi et al. and Kularathne et al. developed smart footwear systems incorporating temperature and pressure sensors, but lacked advanced feature selection or neuro-fuzzy logic for personalized risk profiling. Ming et al. and Bus et al. emphasized telemedical approaches, though their effectiveness was limited by adherence and simplistic data interpretation. In contrast, the proposed system leverages intelligent preprocessing, robust feature selection via CatBoost, and a deep neuro-fuzzy framework for explainable, real-time DFU detection, making it more adaptive and clinically relevant for at-home screening in resource-constrained settings.

C. Limitations and Future Work

While the proposed system demonstrates significant potential, it does face certain limitations that could impact the comprehensiveness of diabetic foot ulcer (DFU) risk assessment. A notable shortcoming is the exclusion of pulse oximeter data and microvascular flow indicators, which are critical for evaluating peripheral circulation and anticipating DFU development. Moreover, the current smartphone-based implementation lacks individualized interpretability tools such as SHAP or LIME, restricting users from understanding the underlying reasoning behind each prediction. Another limitation is the absence of longitudinal tracking, which is essential for monitoring changes in foot health over extended periods.

To overcome these gaps, future iterations of the system will integrate pulse oximeter sensors to support real-time vascular health evaluation. Additionally, efforts will be made to embed SHAP-driven explainability directly into the mobile application, offering both clinicians and users greater transparency into prediction logic. The dataset will also be diversified to include participants from various ethnic backgrounds, thereby improving the model's generalizability and relevance. Furthermore, the architecture will adopt federated learning techniques to facilitate on-device model training while preserving user privacy. Collectively, these enhancements aim to bolster the system's clinical utility, reliability, and adaptability in diverse, real-world healthcare environments.

V. CONCLUSION

This study validates the effectiveness of combining CatBoost-based feature selection with a Deep Neuro-Fuzzy Network (DN-FN) for early and interpretable prediction of Diabetic Foot Ulcer (DFU) risk. By leveraging a hybrid input space of clinical attributes and real-time sensory data—including plantar pressure, foot temperature, and vibration sensitivity—the proposed framework demonstrates superior performance over existing machine learning models in terms of accuracy, reliability, and semantic transparency. The smartphone-integrated deployment ensures offline operability and user accessibility, making it particularly suitable for rural and resource-constrained settings. The system allows patients to input clinical data once while performing periodic sensory tests, enabling continuous foot health monitoring. Comparative evaluation shows that the proposed approach outperforms state-of-the-art models in key evaluation metrics, underscoring its robustness and clinical relevance. Future enhancements will focus on incorporating vascular health sensors like pulse oximeters, advanced explainable AI techniques such as SHAP for instance-level interpretation, and privacy-aware training methods like federated learning to expand its utility and scalability in real-world clinical practice.

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DISCLOSURE OF INTERESTS

The author(s) declare(s) that there is no conflict-of-interest regarding the publication of this paper.

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