# Next-Generation Explainable Sensor-Fusion-Based Artificial Intelligence Framework for In-Home Diabetic Foot Ulcer Risk Prediction

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***Abstract*—Diabetic Foot Ulcers (DFUs) are one of the most serious but preventable complications of diabetes mellitus that often develop without clinical signs until the late stages. This means that neuropathic and vascular abnormalities should be diagnosed in time to be effectively prevented. This study presents the design and development of a home-based smart monitoring system that can be used to identify DFU risk in its early stage by non-invasive sensor-fusion-based monitoring. A baseline version of the system with a plantar pressure sensor and a vibration-based tactile sensitivity evaluation was developed to detect early neuropathic changes in foot health with the use of a composite learning model. Building on this baseline, the proposed framework extends the sensor array with force-sensing resistors (FSRs) to map abnormal plantar pressure regions, vibration motors to evaluate tactile sensitivity, DS18B20 temperature sensors to evaluate dermal thermal variation, and a pulse sensor to evaluate the plantar blood flow. SHAP (SHapley Additive exPlanations) guided RFE (Recursive Feature Elimination) is used to process sensor signals to identify physiologically salient features. One of these is a hybrid Multi-Layer Perceptron-Bidirectional Long Short-Term Memory (MLP-BiLSTM) model with a fuzzy inference layer that then categorizes DFU risk into Low, Medium, and High. Explainable Artificial Intelligence (XAI) methods, such as SHAP and LIME (Local Interpretable Model-agnostic Explanations), are incorporated to increase clinical understandability. Experimental results indicate that the proposed model improves both predictive performance and explainability relative to the baseline methods evaluated, supporting consistent, clinician-interpretable home-based screening of diabetic foot risk within the studied population; broader external validation across additional sites remains necessary before wider clinical generalization can be claimed.**

***Keywords*—DFU risk assessment; sensor-fusion-based monitoring system; Explainable Artificial Intelligence (XAI); MLP-BiLSTM hybrid model; home-based healthcare monitoring***

## I. Introduction

Diabetes mellitus is one of the most widespread metabolic disorders worldwide, and as of 2021, the prevalence of this disease was about 537 million adults in the world, whereas this number is estimated to be approximately 783 million in 2045. The increasing prevalence highlights its burden on general health and the need for more effective preventive and management measures [1]. DFU is one of the most debilitating chronic complications of diabetes that can quickly turn into an infection, gangrene, and, in the most severe cases, amputation of lower limbs [2]. Primary evidence indicates that 15-25% of diabetic patients will experience DFUs at some point in their life, with about 85 percent of all amputations relating to diabetes coming after the development of the ulcers [3]. DFUs have become a major source of hospitalization, morbidity, and disability in India, especially among the elderly and rural population, with a prevalence of diabetes in over 77 million adults in India [4]. The mortality rate from DFUs was estimated to be 30-40 years, which is similar to the number of malignancies, which, in turn, observes the first cases of DFU infection and constant risk monitoring extremely important [5]. However, it is difficult to diagnose in time, particularly in those places where clinics are inaccessible, subjective assessment is among the possible ones, and the instruments of continuous monitoring are not affordable [6].

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## II. Background

Traditional approaches like monofilament tests and thermography require clinical knowledge and do not provide real-time quantitative data on ulcer progression. In turn, studies have paid more attention to wearable and home-based smart systems that combine sensor technologies with artificial intelligence in order to enable continuous monitoring and the detection of early risk [7].

Late diagnosis continues to worsen ulcers, infection, and result in amputation, especially in semi-urban and rural areas where podiatrist follow-ups are infrequent. As part of the attempt to overcome these challenges, recent studies have examined various methods, such as thermal imaging, plantar pressure mapping, and vibration-based neuropathy assessment, among others. As an example, Early signs of DFUs were found by Eldin et al. [8] through thermal asymmetry indices, whereas Tang et al. [9] and Castro-Martins et al. [10] suggested in-shoe pressure monitoring systems to measure the local plantar load changes. Although these research studies were important towards understanding plantar biomechanics, most of them were based on a single-modality sensing; they lacked vascular analysis and did not use explainable or clinician-oriented frameworks to interpret them.

Remote monitoring and reliance on face-to-face clinical visits are decreasing as new platforms for diabetic care through telemedicine have gained widespread traction following the COVID-19 pandemic [11]. The majority of current methods rely on documenting ulcers via images or patients' subjective responses, rather than on automated, sensor-based

measurements. Equally, wound images and thermal datasets have been used to generate deep learning models [12] [13], but at this point, the subject of focus is visual classification, rather than physical risk prognosis. These models are often black boxes and thus not very interpretable, hence restricting clinical acceptance. The recent explainable AI (XAI) projects in the field of diabetes care, including those by Al-Hudaibi et al. [14] and Islam et al. [15], underline the importance of model transparency, but the application is focused on electronic health records and structured tabular data, rather than continuous multi-sensor data on wearable platforms. Few studies have combined both neuropathic predictors (loss of sensation) and ischemic markers (vascular perfusion) in one predictive system in diabetic foot monitoring. The current smart systems are mainly centered on analyzing plantar pressure and do not involve circulation assessment, and localized vascular profiling at the foot level is not studied much. Moreover, a lot of AI-based models follow the paradigm of single-stage deep learning, which ignores the temporal changes in physiological data, thus missing more subtle progressive changes that can help to identify early ulcer risks.

Based on [16] previous experiment, which used vibration, temperature, and plantar pressure and included a CatBoost-Deep Neuro-Fuzzy Network (DN-FN) model, this study suggests a more refined prototype of the home-based prototype with an added heart rate pulse sensor to measure the plantar venous blood flow, a vital parameter in the assessment of vascular health and predicting ischemic ulcer. The constructed sensor-fusion-based dataset includes vibration sensitivity, plantar pressure, temperature, and pulse, which are processed through SHAP-RFE to obtain interpretable features and subsequently classified with a hybrid MLP-Bi-LSTM model with a fuzzy inference layer. The last system will categorize the DFU risk into low risk, medium risk, and high risk. Moreover, there is the integration of explainable AI (XAI) frameworks like SHAP and LIME, which allow global and local interpretability so that clinicians can interpret the sensor-level factors impacting the model predictions. The developed mobile application, optimized with TensorFlow Lite, performs real-time inference and automatically sends high-risk data to clinicians, providing timely feedback and treatment suggestions. It is a clinician-in-the-loop design that transforms the system into a smart, interpretable, and interrelated healthcare solution that fosters patient awareness and allows expert-based intervention to enable proper management of diabetic foot. The principal contributions of this work can be summarized as follows. First, to the authors' knowledge, this is among the first home-deployable frameworks to combine neuropathic indicators (vibration and pressure) with an ischemic/vascular indicator (pulse-derived plantar blood flow) alongside thermal data within a single edge-inference system; earlier single-modality studies [8]–[10], as well as the authors' own prior baseline [16], did not include this vascular channel. Second, SHAP-RFE is used here not simply to reduce dimensionality but to constrain the retained feature subset to physiologically interpretable variables, which are then passed to a temporally-aware Bi-LSTM branch; pairing clinically grounded feature selection with sequence modelling in this way differs from the static, tree-based feature scoring used in [16]. Third, the fuzzy inference output layer converts model outputs into clinician-legible Low/Medium/High categories that feed directly into a clinician-in-the-loop mobile application, automatically escalating high-risk cases to a physician dashboard - a deployment pathway not present in the cited XAI-for-diabetes literature [14], [15], which is largely confined to retrospective analysis of electronic health records.

## III. Dataset Specification

The samples analysed in this study constitute 316 individuals who were enrolled at the healthcare centers that were located in the Vellore District in Tamil Nadu, India. These included 192 patients who were clinically diagnosed with diabetes and 124 healthy volunteers. The sample, which was produced by this cohort, was heterogeneous, thus making it easier to study the risk of DFU between diabetic and non-diabetic groups.

The data are represented by 40 attributes, separated into 16 demographic, physiological, and lifestyle variables and 24 sensor-derived measurements, as detailed in Table I. The demographic and clinical variables include age, body mass index (BMI) level, a blood level of glycated haemoglobin (HbA1c), blood pressure, family history of diabetes, eating habits, physical activity, smoking, or alcoholism. Together, these parameters provide the contextual health data, which is relevant to DFU risk assessment.

TABLE I. Clinical and Sensor Data Features with Corresponding System Identifiers

| Data Category | Parameters | Identifiers |
|---|---|---|
| Demographics | Age, Gender, BMI, Height, Weight | D-2, D-3, D-4, D-15, D-16 |
| Clinical Markers | Diabetic Status, HbA1c, Blood Pressure, Early DFU Signs | D-1, D-5, D-6, D-14 |
| Lifestyle Factors | Diet, Physical Activity, Smoking, Alcohol | D-8, D-9, D-10, D-11 |
| Social Determinants | Education, Profession, Family History | D-7, D-12, D-13 |
| Sensor Data | Vibration (16 points), Pressure (4 points), Temperature (2 points), Pulse (2 points) | RV-1-8, LV-1-8, RP-1/2, LP-1/2, RT, LT, PR, PL |

## IV. Methodology

### A. Baseline Model: LightGBM-E-ANFIS Framework

The experimental platform was designed to acquire biomechanical and sensory information that was relevant to early diabetic neuropathy. An in-shoe prototype was fabricated, including a force-sensing resistor (FSR) and coin-type vibrators. The 4 FSRs were positioned on anatomically significant plantar locations: the forefoot, the midfoot, and the heel, to record pressure-distribution profiles. Plantar-pressure loading variations were acquired in analog form and digitised through an Arduino Mega 2560 microcontroller, thus enabling aberrant loading asymmetries associated with ulcer-prone areas to be identified.

Sensory impairment was determined based on a series of 16 micro-vibration motors (8 motors per foot) that were placed at physiologically relevant plantar sites, such as the hallux, metatarsal heads, midfoot, and heel. In the assessment

protocol, subjects were asked to self-report their perceptual thresholds through a mobile interface based on the controlled vibratory stimulus (motors). The integrated sensing system simultaneously analyses biomechanical load patterns and neurosensory losses. Both the pressure-loading and vibratory motor metrics were wirelessly transmitted via an HC-05 Bluetooth module to an Android app for further clinical analyses. After data collection, the entire dataset was rescaled via normalised pre-processing, where continuous variables were normalised using the min-max method and one-hot encoding (categorical variables). The features were refined through an Enhanced Adaptive Neuro-Fuzzy Inference System (E-ANFIS) optimised with the help of Ant Lion Optimizer (ALO) [17] [18] [19]. This process removed redundant features and reduced the feature space, which increased model stability and alleviated overfitting.

Light Gradient Boosting Machine (LightGBM) [20] was utilized to classify the risks of DFU due to its computational efficiency and suitability for tabular biomedical data. To ensure high generalisation, the model was trained using stratified five-fold cross-validation. LightGBM produced probabilistic outputs, which were further narrowed by the E -ANFIS model that combined rule-based fuzzy reasoning with neural learning to learn nonlinear associations between physiological variables.

Formally, let $X \in \mathbb{R}^{n\times d}$ denotes the preprocessed dataset represented as a real-valued matrix, where X (preprocessed dataset) consists of $n$ samples (rows) and $d$ selected attributes (columns). Here, $\mathbb{R}$ indicates that all elements of the matrix are real numbers, corresponding to continuous numerical values obtained after the data pre-processing stages. The LightGBM classifier estimates a confidence score $s_i = f_{LGB}(x_i)$ for each sample. This score, together with auxiliary physiological indicators, forms the input vector u for the E-ANFIS system. The model follows the Takagi-Sugeno fuzzy inference model [21], in which the fuzzy antecedents are modeled using the Gaussian membership functions and the terminal risk score is estimated using the linear consequents. The membership function for each input variable is defined as in Eq. (1).

$$\mu_{j,p}(u_p) = \exp\ \left(-\frac{(u_p - c_{j,p})^2}{2\sigma_{j,p}^2}\right), \tag{1}$$

where, $c_{j,p}$ and $\sigma_{j,p}$ denote the center and width of the membership function. The firing strength of rule $j$is determined using the product t-norm [Eq. (2)],

$$w_j = \prod_p\ \mu_{j,p}(u_p), \tag{2}$$

followed by normalization [Eq. (3)],

$$\bar{w}_j = \frac{w_j}{\sum_{k=1}^{m} w_k}. \tag{3}$$

Each rule computes a linear consequent of the form [Eq. (4)]

$$z_j = \mathrm{r}_j^{\top}\mathrm{u} + t_j, \tag{4}$$

and the final E-ANFIS output is obtained by weighted aggregation [Eq. (5)].

$$z = \sum_{j=1}^{m}\ \bar{w}_j z_j. \tag{5}$$

The output $z$ is converted into one of the three diagnostic categories using two calibrated thresholds [Eq. (6)],

$$\hat{y} = \begin{cases} 0 & z < \theta_1, \\ 1 & \theta_1 \le z < \theta_2, \\ 2 & z \ge \theta_2. \end{cases} \tag{6}$$

The aggregated output is then mapped into three diagnostic categories representing normal, at-risk, and early DFU conditions. Therefore, the hybrid LightGBM-E-ANFIS framework will combine the strong predictive power of gradient-boosted decision trees with the interpretability of neuro-fuzzy reasoning, enabling reliable, clinically transparent assessment of DFU risk.

### B. *Proposed Sensor-Fusion-Based Explainable AI Framework*

This study aims to improve DFU risk prediction by incorporating vascular, sensory, and thermal modalities into a home-based diagnostic architecture. Building on a previously reported baseline system [16], which incorporated vibration, temperature, and plantar-pressure measurements, the present framework adds a vascular dimension with heartbeat pulse monitoring, which measures the peripheral circulation via the plantar vein. This multimodal sensing scheme allows for a more exhaustive assessment of neuropathic and ischemic signals, which contributes to the timely occurrence of DFU-related complications. The general workflow of the proposed model is defined in Fig. 1.

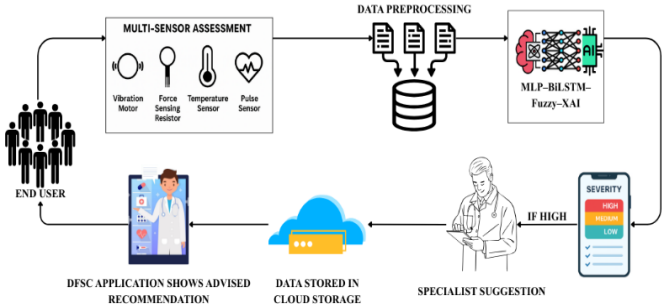


Fig. 1. Workflow cycle of the proposed model.

*1) Data acquisition and sensor integration:* Building on the baseline hardware described in Section IV-A, the sensor array was extended with DS18B20 temperature sensors at the midfoot for localized thermal data and a heart-rate pulse sensor for plantar venous blood flow, in addition to the existing plantar-pressure and vibration channels. All sensors were connected to an Arduino Mega 2560 acquisition unit and transmitted synchronized readings wirelessly via an ESP32 Wi-Fi module to a smartphone application for processing and visualization.

Data pre-processing and feature engineering: Technically, defined pre-processing steps were incorporated to ensure the integrity of the data and the consistency of the analysis. The non-captured numerical values (e.g., BMI, HbA1c, blood pressure) were substituted with the means of existing datasets, and categorical attributes (i.e., diet, smoking, alcohol consumption) with the mode value to retain the population-

level trends. Categorical variables were encoded through a hybrid strategy, wherein binary and ordinal features were transformed via label encoding. To eliminate the artificial ordinal relationships, the nominal variables were represented using one-hot encoding, and continuous variables were normalized using min-max scaling to reduce the influence of inter-subject variance. Pulse signals were divided into short, predetermined windows to extract time- and frequency-domain features for detecting hidden vascular anomalies, which indicate ischemic stress. Vibration responses were processed into sensitivity indices that indicated the number of detectable vibration points per foot, and this denotes neuropathic degradation. The multimodal data, which is formed as a combination of clinical, sensory, and vascular data, becomes a solid basis for the extended refinement of features and classification (Fig. 2).

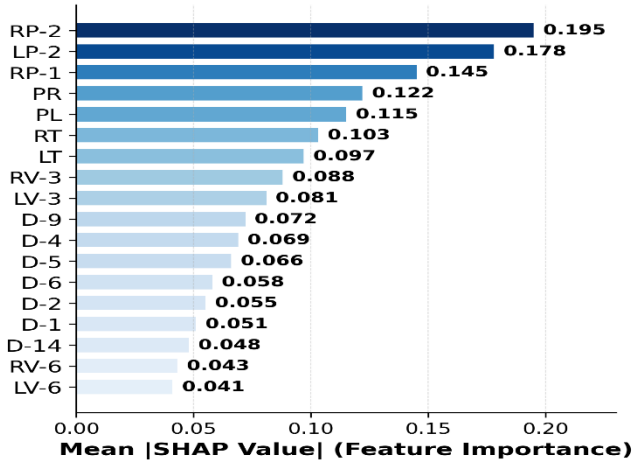


Fig. 2. Feature importance graph of the SHAP-RFE selected features.

*2) SHAP-guided recursive elimination feature selection:* SHAP-RFE [22] was utilized to refine the features for enhancing the interpretability of the model and computational efficiency. SHAP values were used to measure the individual contribution of each attribute to the model performance, and attributes with smaller SHAP values were repeatedly removed through recursive elimination. This process provided an 18-variable subset of the original 40-feature dataset, with each retained variable carrying high clinical and discriminative significance. The subset is dominated by pressure and pulse variables - heel and forefoot pressure at both feet (RP-1, RP-2, LP-2), plantar pulse readings (PR, PL), and bilateral plantar temperature (RT, LT) together with vibration sensitivity at specific plantar sites (RV-3, LV-3, RV-6, LV-6) and a set of clinical and demographic variables (BMI, HbA1c, blood pressure, age, diabetic status, early DFU signs, and physical activity). These retained features are consistent with the neuropathic and vascular mechanisms underlying DFU risk. In comparison to traditional ranking-based approaches, SHAP-RFE combines both statistical robustness and physiological interpretability, so that the refined subset is composed of medically meaningful risk factors of DFU. The output 18-feature input space offers a consistent and interpretable training base for hybrid models.

*3) Hybrid MLP-Bi-LSTM-Fuzzy classification model:* A hybrid architecture of MLP-Bi-LSTM refined dataset was modelled with a fuzzy inference output layer [23] [24]. The MLP module models all the variables that are not organized in time, e.g., clinical parameters and vibration responses; the Bi-LSTM branch models the sequential correlations in the time series of pressure, temperature, and pulse sensors. The bi-directional structure of the Bi-LSTM allows both antecedent and subsequent temporal contexts to be used in learning, thus enhancing the ability to detect small dynamic changes that may be precursors to DFU occurrence. Fig. 3 depicts the general description of the workflow of the proposed methodology.

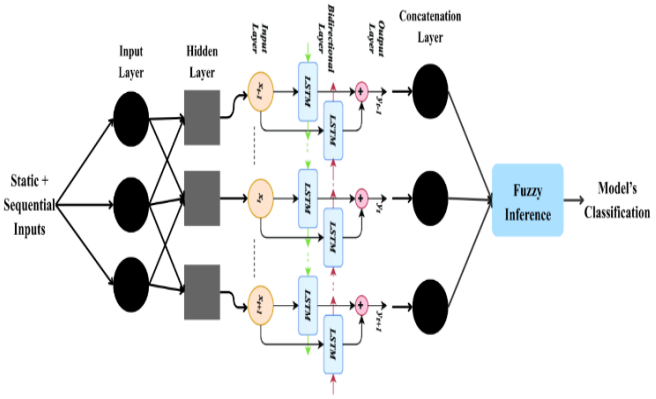


Fig. 3. Hybrid MLP-Bi-LSTM-Fuzzy classification model.

The results of the MLP and the Bi-LSTM branches are merged in a fusion layer, and a single feature vector will be formed, which will then be fed to the fuzzy inference module. This module classifies DFU risk into three linguistic levels: Low, Medium, and High, whereby a smooth transition is achieved between boundary regions with the use of Gaussian membership functions. The fuzzy mapping is a method that converts the numerical results of the deep network into clinically interpretable extremes of severity and thus reconciles model results with the clinical practitioner.

*4) Training the MLP-Bi-LSTM-Fuzzy model and validation:* Categorical cross-entropy loss with adaptive regularisation is implemented to train the hybrid model to maintain a trade-off between sensitivity and specificity of classification. Bayesian optimisation was used to perform hyperparameter tuning and was implemented with the help of the Optuna framework [25] [26], which progressively searched the hyperparameter space of learning rates, neuronal configurations, and regularisation weights. The data were split into 80% training and 20% testing (balanced class distribution), and five-fold cross-validation was utilized to improve generalisation and reduce overfitting.

*5) Algorithm of the MLP-Bi-LSTM-Fuzzy model:*

The pre-processed input vector is determined as being $x_i \in \mathbb{R}^{40}$. The MLP branch computes hierarchical feature representations as given in Eq. (7).

$$h_1 = \sigma(W_1 x_i + b_1), h_2 = \sigma(W_2 h_1 + b_2) \quad (7)$$

as the BiLSTM operates on time-series lengthy sequences $\{s_t\}_{t=1}^{T}$ of pressure, temperature, and pulse measurements, as described in Eq. (8):

$$h_t = \text{LSTM}_f(s_t), \overleftarrow{h}_t = \text{LSTM}_b(s_t), \quad (8)$$

Resulting in a concatenated sequence representation as shown in Eq. (9):

$$h_{seq} = [h_T; \overleftarrow{h}_1]. \quad (9)$$

The fusion layer combines the two representations as in Eq. (10)

$$z = \tanh(W_f[h_2; h_{seq}] + b_f) \quad (10)$$

and the fuzzy membership of each of the classes $c \in \{L, M, H\}$ is stated as [Eq. (11)]

$$\mu_c(z) = \exp(-\frac{||z-\eta_c||^2}{2\sigma_c^2}). \quad (11)$$

The risk is assessed as predicted risk [Eq. (12)].

$$\hat{y}_i = \arg\max_c \frac{\mu_c(z)}{\sum_k \mu_k(z)}. \quad (12)$$

This method combines profound time-based learning and fuzzy reasoning to generate an interpretable probabilistic answer regarding the probability of DFU risk severity. The framework is an adaptive, transparent, and clinician-monitored diagnostic system during deployment. The model provides context-aware predictions to be interpreted and acted upon as clinically necessary by merging vibration, plantar pressure, temperature, and pulse measurements with clinical parameters. Its mobile integration and explainable design provide the ability to monitor constantly, at home, to provide patients with real-time insights and assist in data-driven clinical feedback. In general, the system provides a comprehensive solution for scalable, intelligent, and patient-centred diabetic foot management.

## V. Model Outcomes and Interferences

The clinical trials demonstrate that the proposed system achieves a substantial improvement in predictive accuracy compared with existing frameworks. The addition of the temperature sensor and pulse sensor, which have the potential to monitor abnormal differences in the plantar temperature and peripheral blood flow and circulatory dynamics of the plantar vein, significantly increases the ability of the model to differentiate cases of high-risk diabetic foot ulcer (DFU) that are related to ischemic or vascular dysfunction. This addition significantly decreases the number of false negative identifications of severe conditions that had been hard to identify with the use of vibration motor response and plantar pressure sensor alone.

To achieve this, the quantitative analysis of performance (Fig. 4) indicates that the proposed model positively impacts the estimation of various metrics by 2-3% relative to the CatBoost-DN-FN. This methodology outperforms the other tested architectures, such as CNN-SVM. [27], LSTM-Fuzzy [28]and LightGBM-EANFIS (Baseline), which highlights its strength and capacity to generalise in DFU risk profiling. The high values of area under the receiver operating characteristic curve (AUC-ROC) and Matthews correlation coefficient (MCC) are also consistent and show that the model is stable and reliable when it is used in multi-class classification.

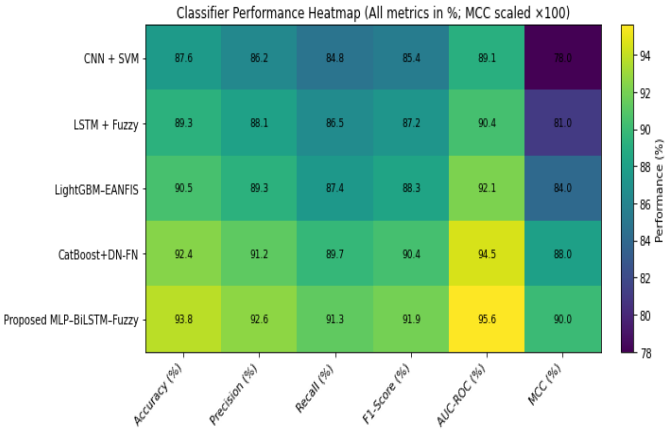


Fig. 4. Heatmap indicating the performance comparison of classifiers.

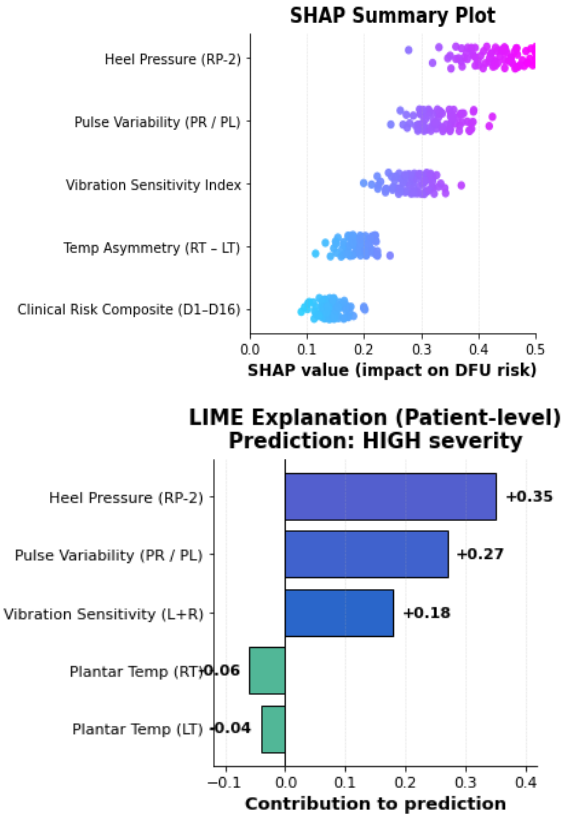


Fig. 5. Global (SHAP) and local explainability (LIME) interpretation analysis of DFU risk profiling from proposed models.

The explainability analysis provides additional clinical information about the model's decision-making process. The summary plots of SHAP (Fig. 5(a)) indicate that the most significant variables for stratifying the risk of DFU are plantar heel pressure, pulse variability, and loss of vibration sensitivity, consistent with existing literature indicating that

neuropathy and ischemic perfusion deficits are the main predictors of ulcer development. The interpretations of cases based on LIME (Fig. 5(b)) also illustrate the influences that sensor inputs have on individual prediction. As an example, in a subject with high risk, LIME detected abnormal pulse amplitude and elevated heel pressure to be leading factors - results that were in line with clinical reports of compromised blood circulation and focal stress build-up. These visualisations provide better model transparency, build clinical trust, and clarify the association between physiological relevance and algorithmic reasoning.

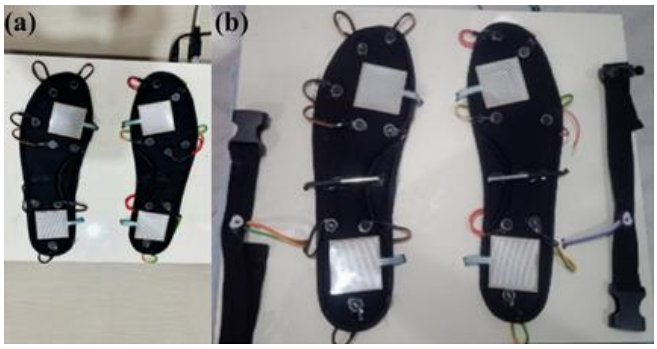


Fig. 6. (a) Baseline prototype. Initial: proof of concept. (b) Feature-enhanced revised prototype (functionality extended).

As a result, the proposed hybrid model achieves a successful distribution of technical accuracy, clinical applicability, and explainable decision support. The combination of vascular, sensory, and thermal capabilities presented in an interpretable deep-learning architecture provides the system with a high predictive accuracy along with the transparency and clinician-interaction needed in the real-world operation of diabetic foot.

## VI. Sensor Assembly and Prototype Implementation

The in-home diabetic foot monitoring system was experimentally tested using an integrated sensor prototype on the basis of the real-time acquisition of physiological data and the evaluation of DFU risk. Fig. 6(a) shows that the experiment had a design with the inclusion of plantar pressure sensors and vibration motors to assess both biomechanical loading and sensory deficits. Based on that design, the present system is designed to combine four different sensing modalities, as shown in Fig. 6(b).

The proposed model prototype includes force-sensing resistors (FSRs) to measure the amount of plantar pressure on the significant anatomical positions, namely, the forefoot and the heel; vibration motors to measure the tactile sensitivity on eight discrete locations along with each foot; DS18B20 temperature sensors to evaluate dermal thermal variations, and heart-rate pulse sensors to estimate the vascular dynamics based on the measurement of the plantar blood flow. The sensing components are all integrated into a compliant insole platform to allow the user to be comfortable in the long term and to ensure accurate monitoring. The sensing modules are each connected to an Arduino Mega 2560 data acquisition board each, which provides the ability to sample synchronized data and low-latency wireless communication.

At every stage of the clinical trial, the participants were made to stand with both feet on the insole platform, and the vibration stimuli were applied in turn at sixteen points of touch (eight on each foot). The participants were asked to report the perception of vibration using the mobile application interface (Fig. 7), and their answers were registered as binary sensitivity responses. At the same time, the system was also recording the real-time plantar pressure, temperature, and pulse data.

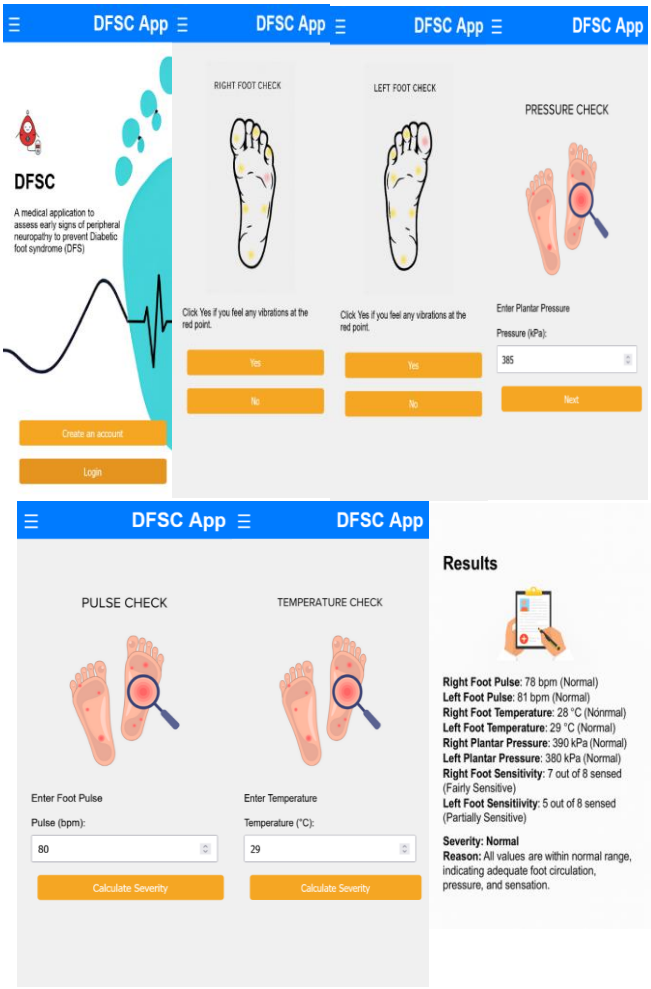


Fig. 7. The DFSC (Diabetic Foot Screening and Classification) mobile application's real-time functionality and user interface.

The recorded metrics of the prototype were wirelessly communicated through an ESP32 Wi-Fi microcontroller to a smartphone application written in Android Studio (Java/Kotlin). The application uses a TensorFlow Lite-optimised hybrid MLP-Bi-LSTM-Fuzzy model that is applied to perform on-device inference for DFU risk prediction. The model has three levels of risk associated with foot health, namely Low, Medium, and High, relying on the combination of sensory and vascular inputs. The mobile application has a simple dashboard, which displays the predicted risk level with major sensor-derived parameters such as the mean number of vibration points detected (out of sixteen), plantar pressure, thermal gradients, and pulse-rate variability.

The real-time testing environment, i.e., the volunteers, the sensor-integrated prototype, and the mobile-application

interface, is shown in Fig. 8. The application on the smartphone also has a clinician-feedback tool, which looks automatic as soon as the High-risk outcome is recognized. The sensor data and interpretability reports are then safely transferred into a physician dashboard through the cloud. The clinician checks the information, confirms the risk level calculated by AI, and offers individual recommendations, including changes in therapy or lifestyle advice, on the same interface.

Fig. 8. The In-situ engagement: captured participants during clinical trials.

It is a clinician-in-the-loop system that creates a closed, continuous feedback loop between patients and healthcare providers, which facilitates real-time monitoring and preventive intervention. The personalised therapy-recommendation module in the application was developed to fit the diverse risk-severity levels. The module was designed and empirically tested to enable a user-friendly interface for feedback and treatment suggestions and has later been integrated and functionally assessed in the application. The treatment recommendation interface is under trial, and further refinements are planned in terms of automated data transmission to the relevant specialist for every patient, allowing for the conduct of context-aware, individualised therapeutic choices based on the evaluated risk of DFU severity. The effective implementation and testing of the system suggest the technical feasibility of the system in continuous and home-based monitoring of diabetic foot health. The prototype has great potential with regard to being a scalable digital-health platform for early DFU risk assessment, and personalised intervention through the combination of multi-sensor fusion, explainable AI, and telemedicine-enabled clinician feedback on a single mobile platform.

## VII. Limitations and Future Clinical Deployment

The cohort examined in this study was drawn entirely from healthcare centres in the Vellore district of Tamil Nadu, and the reported performance figures should accordingly be read as characteristic of this population rather than as evidence of broad clinical generalizability. Diabetic foot presentation can vary considerably with regional diet, footwear practices, and healthcare access, and a system trained on a single-site cohort may not transfer cleanly to other settings without further tuning. Extending the dataset to additional centres, ideally spanning different geographic and socioeconomic contexts, is a necessary step before the framework can be positioned as a general-purpose screening tool rather than a regionally validated prototype.

Deployment readiness raises a related set of questions. The mobile application, the clinician dashboard, and the treatment-recommendation module have all been built and exercised during development, and the underlying model performs reliably on the held-out test data described in Section V. What the current work does not yet include is an independent clinical evaluation - a podiatrist or endocrinologist reviewing the system's outputs against their own diagnostic judgment in a live setting. Functional testing during development is a different exercise from prospective clinical use, and closing that gap through a pilot study involving practising clinicians is the logical next step before the platform could be considered ready for routine care.

Two aspects of the sensing pipeline also warrant caution. Vibratory sensitivity is currently captured through a binary self-report: the participant indicates, via the mobile interface, whether a given stimulus was felt. This is simpler to deploy than standard clinical tools such as the Semmes-Weinstein monofilament test, but it is also more subjective, and the extent to which patient-reported perception diverges from a validated neuropathy assessment has not yet been measured directly. Separately, the pulse and temperature channels are physically the most exposed to everyday use; foot placement, movement during measurement, and ambient temperature can all introduce noise that a single clinical visit would not encounter. Neither source of variability appears to have compromised the results presented here, but neither has been formally quantified across a range of home conditions, and both deserve dedicated attention as the system moves toward wider use.

The interpretability outputs generated by SHAP and LIME are, at present, evaluated on their consistency with known clinical reasoning about neuropathy and vascular risk rather than through direct comparison with clinician judgment on the same cases. A more systematic check asking clinicians to independently rank the risk factors they would expect for a given patient and comparing that ranking against the model's explanations would offer firmer evidence that the explanations are clinically useful rather than merely plausible. Alongside this, expanding the physiological coverage of the system with additional modalities such as SpO2 monitoring or sweat-based biosensors, and exploring federated learning approaches that would allow multiple sites to contribute to model training without centralising patient data, represent natural directions for extending this work toward a more broadly deployable and clinically grounded platform.

## VIII. Conclusion and Prospects

This study presents the evolution of an in-home diabetic foot ulcer monitoring system, from an initial biomechanical sensing approach to a multi-sensor, explainable AI-based platform. The baseline version combined plantar-pressure and vibration measurements with a LightGBM-E-ANFIS classifier to detect early signs of DFU risk. While this baseline demonstrated meaningful potential for detecting neuropathic changes, the present study extends it substantially through the addition of thermal and vascular sensing and an explainable

deep-learning architecture. The augmented system combines vibration, pressure, temperature, and pulse data to support a more comprehensive analysis of the neuropathic and ischemic biomarkers relevant to DFU pathogenesis. The optimised MLP-BiLSTM-Fuzzy model, guided by SHAP-RFE feature selection, captures the nonlinear relationships, temporal dynamics, and uncertainty inherent in physiological sensor data, while the integration of SHAP and LIME increases the transparency of model predictions for clinicians reviewing the mobile application interface. The accompanying clinician-feedback pathway further supports the system's practical relevance for preventive healthcare delivery.

As discussed in Section VII, several open questions remain around external validation, prospective clinical assessment, and quantitative evaluation of explainability, and these will guide the next phase of this work. Overall, the system illustrates a feasible pathway toward a proactive, interpretable, and clinician-connected platform for long-term, personalised diabetic foot management.

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## COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

## ETHICAL APPROVAL

This study involved human participants who were interviewed as part of a non-interventional observational study. No clinical procedures, experiments, or interventions were performed at any stage of the research. Before participation, written informed consent was obtained from all individuals after explaining the purpose of the study and their right to withdraw at any time.

To ensure confidentiality and protect participant privacy, all individuals are identified only by pseudonyms in the manuscript and related publications. The study protocol was reviewed and approved by the Institutional Ethical Committee for Studies on Human Subjects, Vellore Institute of Technology (VIT), Vellore, under the approval reference VIT/XIII IECH/12, dated March 10, 2023, following the committee meeting held on March 04, 2023.

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