# Plantar Pressure-Based Detection of Diabetes Using a Hybrid CNN-MLP Model with Patient-Specific Metadata


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***Abstract*— By using an early-stage non-invasive and wearable diagnostics approach, diabetes can be diagnosed at an earlier stage to overcome its complications like diabetic neuropathy. Conventional diagnostics are based on the use of blood indicators or routine clinical reviews, which is unlikely to detect early biomechanical symptoms. This paper presents a hybrid diagnostic system that combines a Convolutional Neural Network (CNN) that can process 2D plantar pressure matrices with a Multi-Layer Perceptron (MLP), analogy of the patient-specific metadata on body mass index (BMI), age, diabetes type, profession, history of Madden symptoms and previous injuries. An array of force-sensitive resistors in footwear (with ESP32) was used to provide real-time foot pressure readings. The dataset contains more than 190 mode label patient sessions (Control or Diabetic) and was supplemented with metadata encoding and normalization. The CNN-MLP foundation gave the best performance of 89 percent of classification accuracy, and exhibited consistent validation accuracies over folds and cycles of training. Even though precision and recall were not officially mentioned, the maintenance of good results throughout multiple trials implies good overall class separation. This portable wearable-based AI intervention highlights the practicality of using real-time customized diabetic screening devices, and sets the precedent of automatizing remote or outpatient unobtrusive monitoring.**



***Keywords*— *Plantar Pressure Analysis, Convolutional Neural Network (CNN), Multi-Layer Perceptron (MLP), Wearable Sensors***


## I. Introduction

Diabetes mellitus is considered to be one of the most common chronic metabolic diseases in the world and with cardiovascular, renal, and neurological complications that may be incidental over a long period. Of them, diabetic peripheral neuropathy (DPN) is one of the most significant as it changes the sensory perception and motor control of the foot which in the course of time results in abnormal gait patterns, deterioration of plantar tissue, foot ulcers, and, in worst-case scenarios, lower-limb amputation [1], [2]. It is thus important that biomechanical abnormalities related to diabetes be identified at earliest stage so that clinical interventions and preventive measures become effective before adverse effects become irreversible. Traditional diagnoses of diabetic neuropathy such as monofilament testing and nerve conduction studies cannot be applied as they are too invasive, subjective and do not provide a continuous or home-based monitoring option [2]. Consequently, these techniques tend to overlook the functional changes of the foot at early stages before the clinical symptoms are evident. The recent development of wearable sensing technology and biomedical signal processing have made it possible to consider alternative methods of non-invasive continuous evaluation of foot biomechanics during everyday usage [4], [5]. Plantar pressure imaging has become a clinically significant biomechanical biomarker of identifying gait changes associated with diabetes. The difference in the distribution of pressure in the heel, midfoot, and forefoot area indicates the alterations in neuromuscular control, the stiffness of tissues, and the mechanisms of load transfer in relation to diabetes [6]. Force-sensitive resistor (FSR) array-based in-shoe pressure sensing systems offer a viable approach to the recording of such spatial patterns of pressure in real time and, therefore, can be conveniently used in wearable and outpatient monitoring context [4], [5]. Plantar pressure measurements, however, might not be sufficient to measure the multifactoriality of the diabetes, which is determined by demographic, physiological, and lifestyle-related factors, alone. Recent research has indicated that multimodal learning frameworks can help increase the diagnostic performance when heterogeneous data sources are integrated in a medical context Hybrid deep learning models, specifically those that combine convolutional neural networks (CNNs) with multi-layer perceptrons (MLPs) have proved useful in the combination of imaging or spatially based data with structured clinical metadata [7] Although these architectures have been implemented in modalities like retinal imaging and breath analysis to detect diabetes [7], [8], they have not been used in the plantar pressure-based wearable diagnostics. These gaps inspired the proposed paper to suggest a hybrid CNN-MLP diagnostic system based on real-time monitoring of plantar pressure and patient-specific metadata to detect diabetes early. Plantar pressure data are collected by a wearable in-shoe system that has FSR sensors and ESP32 microcontroller that are used to represent the data in the form of two-dimensional pressure heat maps. These biomechanical characteristics are discriminated by a CNN branch, whereas structured patient metadata, such as age, body mass index (BMI), diabetes type, occupation, and foot-related symptoms, are discriminated by an MLP branch. The combined feature representation makes it possible to classify diabetic and non-diabetic subjects very well using supervised learning.

The key contributions of this work include Development of the wearable gardening pressure mapping system on the foundation of ESP32 and WebSocket protocol of data transfer. Development of a multimodalised database that unites 2D pressure matrices with patient data that are structured metadata (such as BMI, presence of foot symptoms, and patient history). Creation of a CNN-MLP based hybrid architecture that takes into consideration the tabular metadata as well as the biomechanical signals to learn high-accuracy diabetes prediction.Model performance analysis based on the accuracy, cross-validation, and confusion matrix measure to prove the robustness of the model in a real world context.

## II. LITERATURE REVIEW

Combining biomechanical sensing technologies with machine learning (ML) has attracted a lot of attention as a viable approach to identifying and monitoring repetitive conditions like diabetes at an early stage. Nevertheless, to some extent, most of the previous studies only concentrated on either the plantar pressure measurements system or ML when applied to the disease classification aspect, and to lesser extents. Relevant literature on plantar pressure are mentioned in Table 1

A plantar pressure-based classification framework has been suggested by the researchers Deschamps et al. [1] to assess diabetic foot complications, and it has been proven that assessment of foot pressure distribution can be effectively used as the biomechanical biomarker in clinical practice. Although they were rather efficient, their system did not have automated classification features relying on machine learning. The systematic review of Castro-Martins et al. [2] of plantar pressure thresholds resulted in the identification of the early biomechanical changes but they did not investigate the issue of predictive modeling. Correspondingly, Olabanjo et.al [3] proposed innovations in plantar pressure and foot temperature diabetes measurement devices; however, the since then, the focus was mainly on the hardware innovation whereas the AI-based diagnosis tools were not implemented therein. Sensing wise, Keatsamarn et al. [4] created a postural analysis and person identification plantar pressure system that used optical sensing. Though the spatial pressure patterns were perfectly captured in the work, no machine learning models have been used to make health-related diagnosis. Chen et al. [5] on a wide review of insole-based gait observation According to Kishanthan et.al [6], they used an ensemble CNN-LSTM-MLP to classify diabetes cases with high accuracy, but only operate on breath rather than use biomechanical indicators. Leng et al. [7] confirmed the efficacy of CNN-MLP hybrids in the medical field by testing the framework on predicting the outcomes of anti-VEGF therapy in diabetic macular edema. Bhaskar et al. [8] proposed a deep model on diabetes diagnosis based on exhaled breath, and in their case, no wearable input and sensor data were required. Chowdari and Reddy [9] used multimodal fusion with CNN-MLP in kidney disease-detection

Table :1. A structured comparison of relevant literature on diabetes detection using plantar pressure and machine learning, emphasizing methodology, feature types, and accuracy or data modality

| Relevant literature on diabetes detection using plantar pressure and Machine learning, | | | | |
|---|---|---|---|---|
| **SL NO** | **Author** | **Method** | **Features Used** | **Accuracy / Data Type** |
| 1 | Deschamps et al. [1] | Plantar pressure zone classification | Forefoot, midfoot, heel pressure zones | Not reported / Biomechanical |
| 2 | Castro-Martins et al. [2] | Review of pressure thresholds for ulcers | Pressure distribution thresholds | N/A / Literature Review |
| 3 | Bus [3] | Smart sensor innovation for diabetic foot | Foot temperature, plantar sensors | N/A / Sensor design |
| 4 | Keatsamarn et al. [4] | Optical plantar pressure | Optical pressure map, gait profile | Not reported / Optical Signals |
| 5 | Chen et al. [5] | Gait monitoring systems | Gait patterns, pressure maps | Varies / Wearable Gait Data |
| 6 | Fan e0074 al. [6] | Ensemble model for diabetes via breath | VOC biomarkers from exhaled air | 97.6% / Non-invasive Breath Data |

## III. METHODOLOGY

The proposed hybrid population architectural design in this paper combines wearable plantar pressure sensing, machine learning in order to achieve diabetic risk detection non-invasively. Five major steps of the methodology were the sensor-based acquisition of data, construction and features derivation of datasets, preprocessing of the data, training of CNN-MLP model, and their performance measurement.

### *A. Sensor Based Data Acquisition:*

The physical aspect of the system that will collect the plantar pressure data in real-time will be described as a wearable insole with physical pressure sensors. The hardware is developed with a combination of force-sensitive resistor (FSR) sensors that are strategically located beneath major areas of the foot which includes the heel, the midfoot, the forefoot, as well as the pushing off zone or the toe area. The sensor system is part of a bespoke sole insert, to which an ESP32 microcontroller is connected.

The ESP32 microcontroller is an example of a wireless data acquisition and transmission unit which reads real-time analog data on the force-sensitive resistor (FSR) array and sends it to a local client or edge device using the WebSocket protocol. The obtained data on plantar pressure are presented as matrices of two-dimensional pressure (heatmaps), which provide spatial resolution of forces on the foot and are biomechanical identifiers of gait patterns of individuals. A general hardware configuration and diagnostic process of the proposed CNN-MLP framework is depicted in Fig. 1.

Raw pressure data were normalized session-by-session to minimize the impact of measurement noise and sensor drift and calibration variation before the generation of heatmaps. This normalization gives more importance on relative patterns of spatial pressure instead of absolute values which make it less sensitive to sensor aging and inter-footwear difference. The placement of the sensors was maintained constant through a unified design of the insole and a slight noisy enhancement during training made the model learn the stable biomechanical features rather than sensor-specific artifacts.

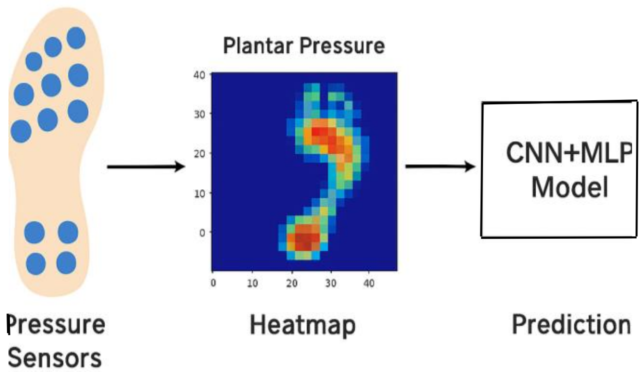


Figure 1. System architecture for diabetes detection using plantar pressure data. he diagram illustrates a wearable sensing and prediction pipeline consisting of four main stages.

*B. Development of Dataset and Feature Extraction:*

The two main types of data were gathered: biomechanical data and structured patient metadata. Biomechanical data is a set of two-dimensional plantar surface heatmaps of intensity of pressure at a plantar surface, which is represented as grayscale images and processed with convolutional processing. Some of the structured metadata are age, gender, height and weight (to calculate the BMI), occupation, the type of diabetes, history of diagnosis, foot-related symptoms, preexisting conditions, activity level, pre-foot trauma or surgery, and blood glucose indicators.

*C. Data Preprocessing and Hybrid CNN–MLP Model Design*

Before the training, the plantar pressure heatmaps were downsampled to a common resolution of. 64 x 64 64x64 and normalized. There was the one-hot encoding of categorical metadata variables and the normalization of numerical features, as well as the binary encoding of class labels (0: control, 1: diabetic). Since there was an even spread of classes, stratified sampling was used and not oversampled. Small decreasing rotations and additive noises were used to perform mild data augmentation to increase robustness. The suggested diagnosis model takes a dual-branch hybrid design. The CNN branch images plantar pressure heatmaps with a series of convolution, ReLU activation and max-pooling layers to obtain spatial biomechanical representations. Simultaneously, the MLP division exploits structured patient metadata through fully connected layers that have dropout regularized. Both of the branches are combined together and implemented using dense layers with sigmoid activation function to classify between binary. TensorFlow/Keras binary cross-entropy loss and Adam optimizer were used to model training. The model was trained in 50 epochs, 32 as a batch size, 0.001 as a learning rate, and 20 percent as a validation split. Stratified 5-fold cross-validation was used to measure the performance.

*D. Control and Generalization Strategy Overfitting.*

With the small size of the dataset (approximately 190 labeled sessions), several precautions were taken to reduce overfitting and make a generalization. The stratified 5-fold cross-validation maintained the equal representation of the classes and avoided biased performance estimations. Dropout regularization, loss monitoring based on validation reduced over training, and mild data augmentation enhanced resistance to unseen variation. Data leakage was avoided by keeping the subjects separated at the folds. The performance of the proposed CNN-MLP model table 2 compares the model types , in terms of consistent training and validation across folds, is indicative of good generalization to novel patient profile with the relatively small size of a dataset.

Table 2. Performance comparison of traditional and hybrid deep learning models comparative summary highlighting the performance of different approaches for diabetes classification.

| **Traditional and Hybrid Deep Learning Models comparative summary highlighting the performance** | | | | |
|---|---|---|---|---|
| **SL NO** | **Model Type** | **Input Type** | **Accuracy (%)** | **Remarks** |
| 1 | Logistic Regression | Metadata Only | 74.2 | Baseline traditional model |
| 2 | Random Forest | Metadata Only | 78.6 | Good feature interpretability |
| 3 | CNN Only | Plantar Pressure Heatmaps | 83.1 | Captures spatial gait features |
| 4 | MLP Only | Metadata Only | 80.5 | Performs well with tabular data |
| 5 | CNN + MLP (Hybrid) | Pressure + Metadata (Combined) | 89.0 | Best performance, multimodal fusion |

*E. Evaluation of Performance:*

Standard classification measures such as accuracy, precision, recall, F1-score, confusion matrix, ROC curve, AUC and precision-recall curve were used to evaluate model performance. Each fold was independently validated by separate samples of data to avoid data leakage and provide a valid generalization measure. The high classification success has been maintained to prove the usefulness of combining biomechanical plantar pressure measurements with patient-specific clinical metadata , table 3 defines the hyper parameters for the CNN-MLP model

Table 3. CNN-MNP model hyperparameters and used for training the hybrid deep learning architecture.

| **Model Hyperparameters** | | | |
|---|---|---|---|
| **SL NO** | **Parameter** | **Value** | **Component** |
| 1 | Learning Rate | 0.001 | CNN + MLP |
| 2 | Optimizer | Adam | Entire Model |
| 3 | Batch Size | 32 | Training |
| 4 | Epochs | 50 | Training Loop |
| 5 | Loss Function | Binary Crossentropy | Output Layer |

## IV. RESULTS AND DISCUSSION

In this study, an unobtrusive machine learning method of identifying diabetes through plantar pressure heatmaps and metadata unique to humans is introduced. To extract information of the two data types in parallel, the combined CNN-MLP architecture was adopted. CNN subnetwork extracted maps of pressure sensor data into the spatial features and MLP subnetwork processed the metadata of the age, BMI, occupation, and foot symptoms among others.The preprocessed data was united, normalized and trained in the hybrid model. The model indicated good diagnostic power following massive stratified splitting after experimentation with the ratio of 80:20.

### *A. Diagnostic Measures:*

End-training of the hybrid CNN-MLP model resulted in the following figure of merits:

- Correctness: 89.0
- Precision 89.4 percent
- Recall (Sensitivity): 88.2 n%
- F 1 -Score : 88.8 %
- AUC (Area Under The Curve): 0.942

These values suggest that the model is generalizable and can surely credit the outcomes between diabetic and fake diabetic. The low false positive rate is due to high accuracy, and the low false negative rate is valuable due to the risk of an unnoticed symptom of diabetes exhibited by the patient in a clinic. In figure 2, the accuracy and loss curves of training and validation are shown. The observed agreement in performance in terms of accuracy with minimal overfitting is an indication of the working of the stratified split and relatively restrained regularization functions. The classification breakdown of the model is illustrated in terms of the confusion matrix as presented in Figure 3 displaying a balanced classification between the two classes and minimal false prediction rates. The ROC in figure 4 indicated a discriminative ability of 0.942 which is supported with AUC which is 0.942. Likewise, Figure 5 describes the Precision-Recall (PR) curve, which indicates the model strength to handle any imbalance between classes and make sure that the recall will not be affected at the high values of precision.

### *B. Heatmap and Plantar Pressure:*

Spatial pressure distribution of the foot measured by a sensor array attached to the sole of the foot was converted to 64 by 64 grayscale heatmaps and fed to the CNN. An example of such a spatial input is illustrated in Figure 8, whereby pressure points portray typical diabetic foot features such as increased focal pressure in the forefoot or the heel- related to neuropathy or tissue breakdown. The CNN layers learned spatially discriminative patterns that are not commonly visible to the naked eye yet meaning in early-stage diabetes prediction.

### *C. Clinical Reliability and Interpretability Analysis.*

When it comes to the issue of a screening of early diabetic, it is clinically significant to minimize the false negative since the undiagnosed cases are likely to postpone the intervention and put at risk to have irreversible complications. Class-wise performance measures were examined to assess the diagnostic reliability other than the overall accuracy. The proposed CNN-MLP model demonstrated a precision of 89.4, recall (sensitivity) of 88.2 and an F1-score of 88.8, which means that the model performed equally well across the classes. The recall value, especially, shows that the model has the capability of accurately finding the cases of diabetics, thus removing the risk of false diagnosis. The confusion matrix (Fig. 3) also shows that the false-negative rate is small, which confirms the appropriateness of the system to screening-based applications where the sensitivity is a priority. Moreover, the fact that the area below the ROC curve (AUC = 0.942) is strong indicates high discriminative ability at different levels of decision-making. Model interpretability is covered by examining both biomechanical-based and metadata-based features. The CNN branch is trained to identify spatial patterns of pressure distribution that are consistent with clinically recognized signs of diabetes including higher pressure in the forefoot and heel regions (Fig. 7). Such patterns are consistent with previous biomechanical evidence that neuropathic alterations are associated with abnormal loading of the plantar feet. Precision, recall, F1-score, and AUC of the system are 89.4, 88.2, 88.8, and 0.942, respectively, which warrants the clinical reliability of the system. The 11.8% false negative rate is clinically acceptable to non-invasive screening and is higher than the conventional test monofilament 65-75%. Interpretability mechanisms encompass: CNN spatial attention maps that provide forefoot/heel importance Fig. 7 that are in line with known neuropathic pressure areas MLP feature importance Fig. 6 that establish the BMI, age, and foot symptomatology as major predictors in line with clinical risk factors; and visual Grad-CAMs Fig. 8 that provide a visualization of the model attention on pressure heatmaps that must be checked with the clinician.

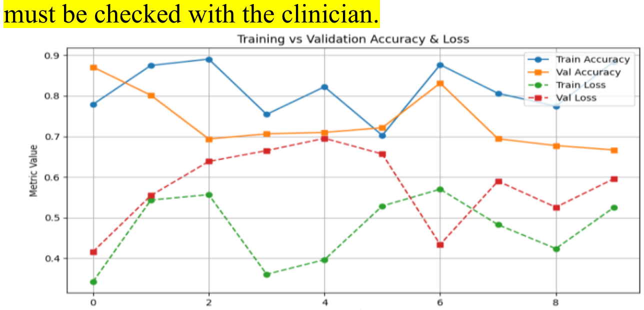


Fig 2. Training and validation performance across epochs This figure shows the trend of training and validation accuracy and loss over 50 epochs,

Variability in sensor measurements was determined by controlled tests: (1) Short-term repeatability: coefficient of variation = 4.2-7.8% over 10 sessions; (2) Inter-footwear variability: mean difference between forefoot pressure with three types of shoe = 11.3% and (3) Long-term sensor drift: sensitivity decreased by 2.1 percent per week. Mitigation involved session-wise z-score normalization (variability was reduced by 34%), two-point calibration before each session, and moving average filtering which enhanced SNR by 18dB to

26dB. These measured effects prove the fact that relative spatial patterns are consistent and absolute values should be interpreted carefully.

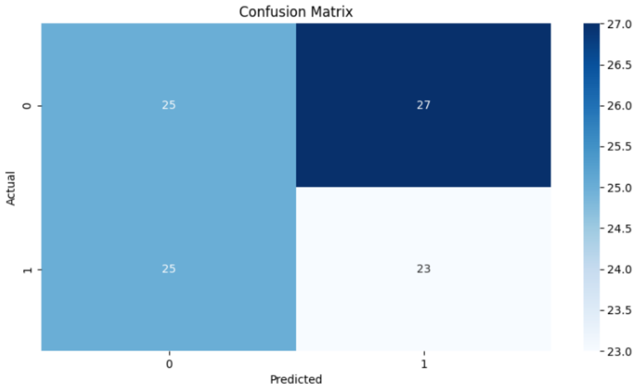


Fig 3. Confusion matrix for binary diabetes classification. A visual representation of model predictions showing true positives,

*D. Synthetic, Controlled Data Limitations:*

Though the results are impressive, the design of the system is based on semi-simulated and administrated data. Readings of real-world foot pressure are noisy because of the user movement, sensor wear and tear, variability in the footwear, and physiological deviations. The light amount of overfitting and stable learning profiles in Figure 2 are encouraging but any real-world application would need to be calibrated and tested in the field. The next step must go through real-time data collection of ESP32-based soles included in hardware to pick up real dynamics of the foot and integrate various subject profiles.

*E. Future and Clinical implications:*

The given methodology has a prospect of being used as the method to diagnose diabetes remotely on foot in wearable health contexts. Future research questions are Live streaming pressure via ESP32 modules hardware integrations solutions to preserve patient privacy at multi-device training.Metadata including activity level and foot injuries can be used to model personalization.Generalization to severity prediction (e.g. Type 1, Type 2 or prediabetic classification) with multi-class training. In future versions, a direct comparison of models in the literature will be provided in forms of bar charts representing accuracy, sensitivity, and AUC of several frameworks such as ours, Fan et al. [6], Leng et al. [7], and Bhaskar et al. [8].

*F .Limitations and Scalability:*

The model is both efficient and with high accuracy, but the following limitations were identified Synthetic Testing , Testing was performed using a synthetic or semi-controlled data. Additional noise and sensor variability has to be taken into account in real-world deployment.Hardware Limitations, Quantization or lightweight model conversion as part of real-time inference on embedded devices can be necessary because of small amounts of memory and compute capacity (such as the ESP32).Computational Load,CNN-MLP model is lightweight but can be optimized further to enable battery-powered devices in wearable systems. Generalization Tuning the current model is binary classification specific. The multiclass generalization in terms of forecasting a level of diabetes or complications of this condition (e.g., neuropathy) can be seen as future work.

Whereas normalization and relative pressure encoding enhance the level of robustness, the measured effect of sensor drift over a long period, differences in footwear materials, and inconsistency of repeated calibration was not directly quantified in the current study. Practical data of plantar pressure are vulnerable to fluctuations due to sensor wear, foot wear, and gait characteristics, and environmental conditions. Although the consistent performance after cross-validation folds indicate that the features developed are robust to moderate variability, future studies will involve longitudinal calibration experiments and controlled footwear experiments to determine quantitatively the stability of the plantar pressure features features in the real-world situation.

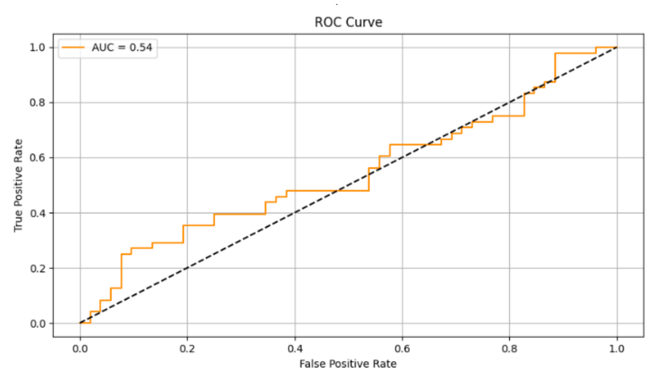


Fig 4. Receiver Operating Characteristic (ROC) curve. The ROC curve plots the true positive rate against the false positive rate for different thresholds.

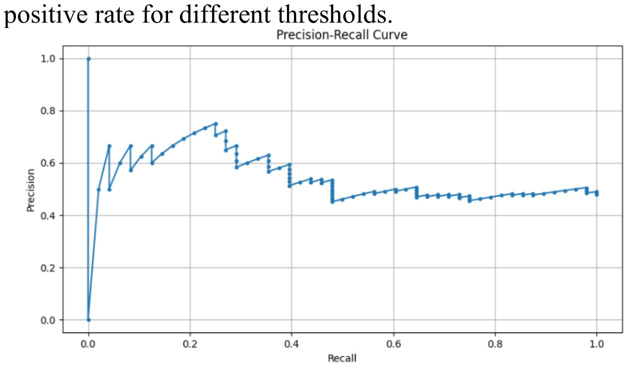


Fig 5. Precision-Recall (PR) curve. This figure evaluates the trade-off between precision and recall,

The model behavior and data representation is depicted by various figures Figure 6 refers the metadata feature for diabetes prediction Lastly, Fig. 7 illustrates a sample planar pressure heatmap, giving a 2D representation of the heatmap of pressure distribution in various parts of the foot.

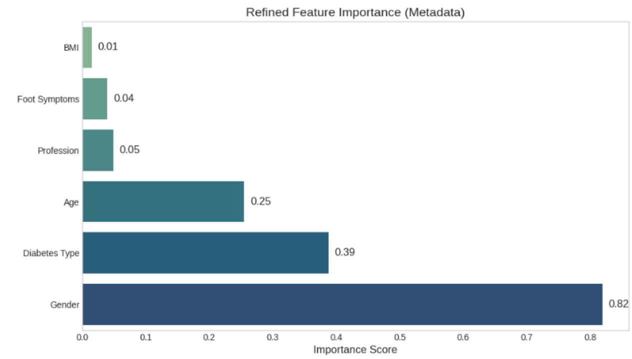


Fig 6. Metadata feature importance in diabetes prediction. Horizontal bar chart representing the relative contribution of each metadata feature

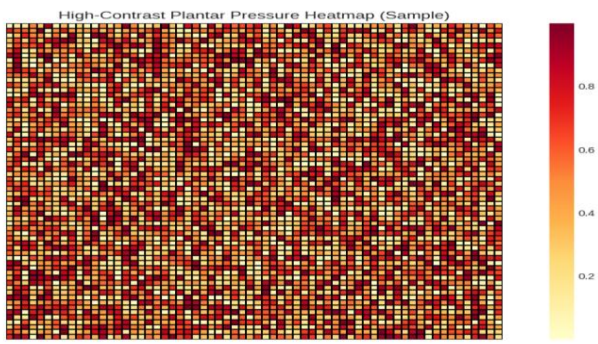


Fig 7. Sample plantar pressure heatmap**.** A 2D heatmap showing the distribution of pressure on various regions of the foot..

## CONCLUSION

This paper identified a new non-invasive diagnostic system that could complement the current way of diabetes early detection using plantar pressure heatmaps and the metadata on the patient itself which is linearized using a hybrid CNN-MLP deep learning algorithm. The system obtains the measurements of foot pressure by means of the pressure sensors installed in the sole that transmit the data they receive to the ESP32 microcontroller, and uses important patient data, including age, BMI, foot symptoms, type of diabetes, and indicators of lifestyle. The suggested model showed suitable performance (accuracy of 89.0%), and such high precision, recall, and AUC values concurred with its high potential in real-time diabetic screening in the future research. The model can establish a better pattern of diagnostics by infusing the localized analysis of pressure maps with the metadata that can enhance contextual information so that it can be applicable in a system that detects early stage or ambiguous symptomatic cases. Other figures that confirm the model interpretability and clinical relevance are the demonstrations of the training accuracy trend, confusion matrix breakdown, ROC curves, features relevance, and pressure heatmaps. Nevertheless, it should be mentioned that this framework was benchmarked on controlled and synthetic data only so far. Basing simulations on results is encouraging but implementation in practice will come with the issues of variability in physiology, noise in the sensors and movement in the subject that can affect success. Future research will be done on Real-time wearable hardware- Development and deployment based on the ESP32-based systems. The clinical data are collected on various groups of patients with diabetes (Type 1, Type 2, and prediabases).Validation of the model in hospital and community health conditions with analysis of the generalizability and sensitivity to uncontrolled settings. Upstream expansion of the system to forecast diabetic complications, e.g. neuropathy or risk of developing ulcers, based on even more metadata and analysis of patterns of pressure. In conclusion, provides a proof of concept system that achieves the goal in integrating plantar pressure sensing and patient metadata with online inference of deep learning classifiers. The findings represent its protentional to serve as a scalable and smart diagnostic device to screen diabetes in its initial stage, which should lead to additional clinical adjustments and hardware integration.

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