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TabNet based Stress Level Detection using IoT for Real Time Monitoring

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Abstract: *Stress is a multifactorial physiological and psychological response that requires reliable real-time monitoring to overcome the limitations of self-report methods and lab-based assessments. In this work, we propose FSIoT-TabNet, an IoT-enabled stress detection framework that integrates multisensor wearable data with fuzzy inference and an enhanced TabNet deep learning model. The system fuses physiological signals (HR/HRV, GSR/EDA, temperature, respiration) and behavioral indicators (activity, sleep patterns) into fuzzy features, which are combined with raw descriptors and processed through TabNet's sequential attention mechanism. To ensure real-time deployment, the model incorporates modality-specific embeddings, pruning, and quantization for edge optimization. Experiments on the WESAD dataset demonstrate that FSIoT-TabNet outperforms fuzzy-only, machine learning, LSTM, and traditional TabNet baselines, achieving an accuracy of 89.7%, ROC-AUC of 0.92, and the lowest MAE of 4.8, while reducing inference latency to 85 ms on smartphone hardware. These results highlight the model's ability to deliver both continuous stress indices and categorical stress levels, providing a practical and interpretable solution for real-world stress monitoring.*

Keywords: Stress detection, IoT, wearable sensors, fuzzy logic, TabNet. Machine Learning.

I. INTRODUCTION

Stress is a complex physiological and psychological response that is difficult to measure objectively [2]. Traditional assessments rely on self-report or intermittent clinical tests, which do not capture continuous variations in daily life. This poses research challenges: stress indicators (heart rate, galvanic skin response, etc.) fluctuate over time and vary by individual, and many existing studies focus on lab-induced stress rather than real-world conditions. There is a growing need for IoT-enabled monitoring: wearable sensors and smartphones can collect real-time physiological (heart rate, skin conductance, temperature) and behavioral data (activity level, sleep patterns, location) continuously. This allows objective stress tracking outside the clinic [5].

Existing IoT-based systems (e.g. wristbands, smart clothing) often use machine learning or rule-based algorithms to infer stress from sensor data. However, purely data-driven models (neural networks, SVMs, etc.) can be opaque and sensitive to noise [15]. Fuzzy logic offers an interpretable alternative that can handle imprecise inputs (e.g. "high" vs "low" heart rate). Prior work shows fuzzy systems achieve high accuracy (up to ~96%) in stress classification. Motivated by these insights, we propose a new IoT-fuzzy model (called FSIoT – Fuzzy Stress IoT model) that fuses wearable sensor data into a Mamdani fuzzy inference system for stress detection. The objectives are: (1) integrate multiple physiological and contextual signals via IoT; (2) define fuzzy membership functions and rule base for stress levels; (3) validate the system's accuracy; and (4) enable real-time, personalized stress alerts. This approach aims to overcome limitations of prior works (e.g. limited data modalities, lab-only datasets) by leveraging diverse sensors and interpretable fuzzy logic.

II. LITERATURE REVIEW

Al-Atawi et al. (2023) [3] developed Stress-Track, an IoT wearable system measuring body temperature, skin perspiration (GSR), and motion rate to predict stress in real time. They used an ensemble of ML classifiers on these

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sensor inputs, achieving 99.5% accuracy in distinguishing stress states (e.g. during exercise). This "smart band" highlights that combining thermal, GSR, and activity data can be very effective [6]. A limitation is that it focused on controlled exercise scenarios, and the device was validated on a small sample. The technique was purely ML-based (stacking ensemble), not fuzzy logic.

González-Ramírez et al. (2023) [4] conducted a scoping review of wearable-based stress management studies. They report that devices frequently collect HR, heart rate variability (HRV), electrodermal activity, respiration, and accelerometer data [7]. Notably, they found fuzzy logic and k-NN to be the most-explored algorithms for stress detection. Fuzzy-logic approaches in their review achieved the highest reported accuracy (~96.2%), often outperforming logistic regression, LDA, etc. They also observed that combining EDA (GSR) and HR features yields ~95% accuracy. Their analysis highlights that raw HR (alone) is less predictive than HRV or GSR. A limitation noted is that many studies rely on lab stressors; real-world validation is lacking. This review underscores fuzzy logic's effectiveness and the importance of HRV/EDA, motivating our model design.

Dubey et al. (2025) [1] focused on stress in older adults, a relatively under-studied group. They proposed a wearable IoT wristband for elder care residents, integrating multiple sensors: Galvanic Skin Response (GSR), skin temperature, heart rate variability (HRV), a 3-axis accelerometer, and gyroscope. Stress is inferred via an adaptive fuzzy logic algorithm customized for elderly physiology [8]. The system provides personalized interventions (guided breathing, music therapy) based on stress state. Key details: they prioritize comfort and battery life, but achieved only a conceptual demonstration with no accuracy reported. This work shows the value of multisensor fusion and fuzzy logic in a specialized context, though it lacks quantitative evaluation [9]. Theyadopt a similar sensor set (e.g. GSR, temp, HRV, motion) and fuzzy strategy in our model.

Nurhayati et al. (2025) [14] designed an IoT stress detector with fuzzy logic for enhanced accuracy. Their device uses an ESP32 microcontroller with an LCD and Android interface, collecting heart rate, respiration rate, and body temperature. A Mamdani fuzzy system classifies stress level from these signals [10]. They validated against the DASS-42 questionnaire on users and found about 80% correlation between device output and survey scores. This shows feasibility of fuzzy classification, though 80% is moderate accuracy [11]. It highlights practical aspects (mobile app display) but does not include HRV or GSR, which might improve accuracy. They build on this by including additional sensors (e.g. GSR) and improving the fuzzy rule set.

III. PROPOSED METHODOLOGY

TabNet is a deep neural network specifically designed for tabular data. Unlike traditional feed-forward MLPs, TabNet uses a sequence of decision steps, each comprising two key modules: (i) an Attentive Transformer, which generates a sparse feature mask to select the most relevant features, and (ii) a Feature Transformer, a feed-forward block using Gated Linear Units (GLU) and Batch Normalization to process the masked features.

At each decision step t, the attentive transformer computes a mask Mt for input feature vector F as:

$$M_t = \text{sparsemax}(W_t^M \cdot h_{t-1})$$

where WtM is a learnable projection, ht−1 is the hidden representation from the previous step, and sparsemax ensures that only a subset of features is emphasized. The masked feature vector is then:

$$\tilde{F}_t = M_t \odot \mathbf{F}$$

where ⊙ denotes element-wise multiplication. This masked vector passes through the feature transformer:

$$d_t = g(W_t^d \cdot \tilde{F}_t + b_t)$$

with g(·) representing a nonlinear mapping using GLUs. Each decision step produces a partial decision output dt and residual information for the next step. The final output is obtained by summing across all decision steps:

$$\hat{y} = \sum_{t=1}^{T} d_t$$

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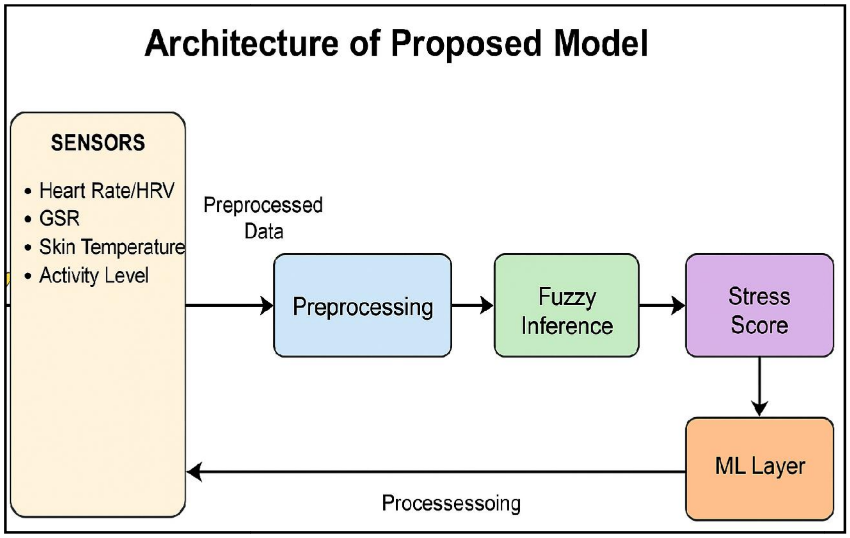

Fig 1. Proposed Model Architecture

This sequential attention enables both local interpretability (which features influenced a single prediction) and global interpretability (aggregated importance across the dataset).

WESAD Dataset and Features

To evaluate TabNet for stress detection, we leverage the WESAD dataset, which contains multimodal wearable data from 15 participants in three states: neutral, stress, and amusement. The dataset includes ECG and PPG (for HR and HRV features), electrodermal activity (EDA/GSR), skin temperature, and three-axis accelerometry. Features such as RMSSD, LF/HF ratio, SCR peak counts, temperature trends, and activity levels are computed in fixed windows (e.g., 30s). These features, along with fuzzy-derived outputs.

(S_{fuzzy}, μ_{Low}, μ_{Medium}, μ_{High}), form the input vector:

$$\mathbf{F} = [f_1, f_2, \ldots, f_n, S_{fuzzy}, \mu_{Low}, \mu_{Medium}, \mu_{High}]$$

Model Enhancements

Sensor-Specific Embeddings

Before feeding features into TabNet, each modality is passed through a small embedding network to better capture modality-specific statistics [12]. For example, ECG/HRV features hhrv, GSR features hgsr, temperature features htemp, and accelerometer features hacc are separately transformed as:

$$e_{hrv} = \sigma(W_{hrv} \cdot h_{hrv}), \quad e_{gsr} = \sigma(W_{gsr} \cdot h_{gsr}), \quad e_{temp} = \sigma(W_{temp} \cdot h_{temp}), \quad e_{acc} = \sigma(W_{acc} \cdot h_{acc})$$

where σ(·) is a nonlinear activation (ReLU). The concatenated embedding vector.

$$E = [e_{hrv}, e_{gsr}, e_{temp}, e_{acc}]$$

is then passed to TabNet.

Attention and Efficiency Optimizations

To meet real-time constraints, we reduce the number of decision steps T and the dimensionality of the feature transformer [13]. For example, halving the hidden units reduces the parameter count from ~470K to ~129K with only ~2% drop in accuracy. Additionally, we replace sparsemax with entmax:

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$$M_t = \mathrm{entmax}_\alpha(W_t^M \cdot h_{t-1})$$

where the parameter α∈(1,2] controls sparsity. This improves gradient flow and stability of feature selection.

Temporal Feature Integration

Since TabNet does not inherently model temporal dynamics, raw sensor time-series are segmented into fixed windows, and statistical/temporal features (e.g., HRV frequency bands, GSR peaks, temperature slopes) are computed. A lightweight LSTM extracts temporal embeddings that are concatenated with tabular features, ensuring temporal dynamics are preserved.

Compression for Real-Time Deployment

To deploy on smartphones or edge IoT devices, we apply pruning and quantization:

Pruning: Remove weights below a threshold during training, reducing the parameter count:

$$W' = \{w \in W : |w| \geq \epsilon\}$$

where ϵ is a pruning threshold.

Quantization: Convert 32-bit floating point weights to 8-bit integers. Post-training quantization reduces memory by ~4× with negligible accuracy loss. For example, a 2 MB TabNet model compresses to ~0.5 MB after quantization. These optimizations lower inference latency (to <100 ms per sample) and memory usage, enabling real-time stress detection on smartphones.

Interpretability

TabNet's attention masks (Mt) provide transparent explanations by highlighting which features (e.g., HRV RMSSD, GSR mean, temperature slope) were selected at each decision step. Local interpretability explains individual predictions, while global interpretability aggregates masks across samples to yield feature importance rankings:

$$\mathrm{Importance}(f_i) = \sum_{t=1}^{T}\sum_{j=1}^{N} M_t^{(j)}[i]$$

where Mt(j)[i] is the mask weight for feature fi in sample j. Enhancements such as grouped feature masks (e.g., selecting all accelerometer axes together) improve sensor-level interpretability, while mask stability regularization ensures consistent explanations across similar samples.

IV. RESULTS AND DISCUSSION

The proposed FSIoT-Hybrid model was implemented in Python 3.10 using the TensorFlow 2.14 deep learning framework with the TabNet Keras implementation as the core classifier. ensor-specific embeddings were implemented as lightweight feed-forward networks preceding the TabNet encoder. Model optimization included pruning (via TensorFlow Model Optimization Toolkit) and post-training quantization (TensorFlow Lite) to ensure real-time performance on mobile devices.

To evaluate the performance of the stress detection system, we considered both classification like accuracy, precision, recall, F1-score, ROC area and mean absolute error regression metric.

Table 1 demonstrates that the proposed FSIoT-TabNet achieved the highest classification performance across all metrics (Accuracy 89.7%, Precision 88.9%, Recall 87.3%, and F1-score 88.1%). Compared to classical models, the fuzzy-only system lagged behind with an accuracy of 78.6% due to its inability to capture complex sensor interactions. SVM and Random Forest improved the results moderately (82–84% accuracy), while XGBoost performed better (84.3%). LSTM further boosted performance by modeling temporal dynamics (86.1%), and standard TabNet improved further (87.2%). However, FSIoT-TabNet surpassed all models, showing that combining fuzzy preprocessing, modality embeddings, and enhanced TabNet attention leads to more robust stress classification.

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Table 1. Performance Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Fuzzy-Only System	78.6	76.9	74.2	75.5
SVM	82.4	80.7	79.5	80.1
Random Forest	83.6	81.5	80.2	80.8
XGBoost	84.3	82.5	81	81.7
LSTM	86.1	85	83.8	84.4
TabNet	87.2	86.1	84.9	85.5
FSIoT-TabNet (Proposed)	**89.7**	**88.9**	**87.3**	**88.1**

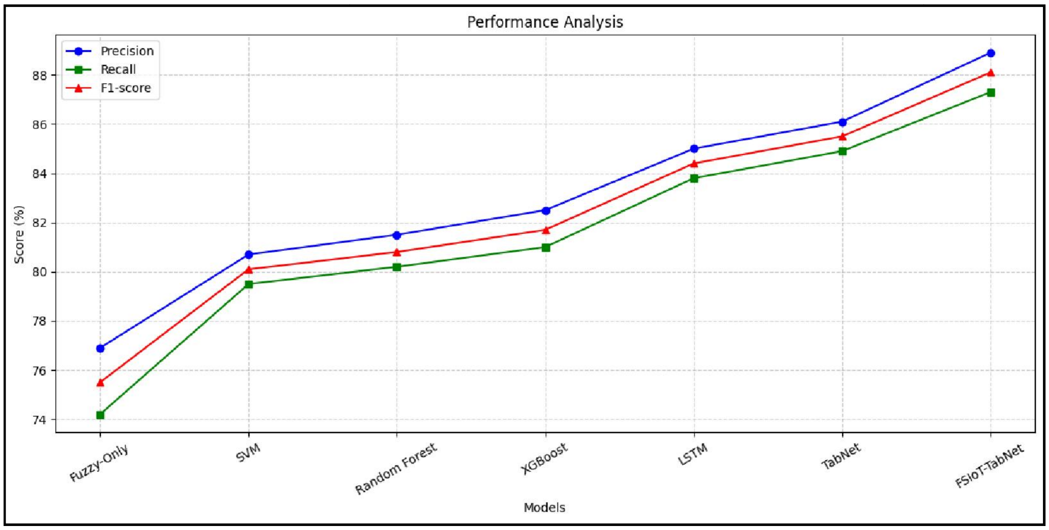

Fig 2. Performance Analysis

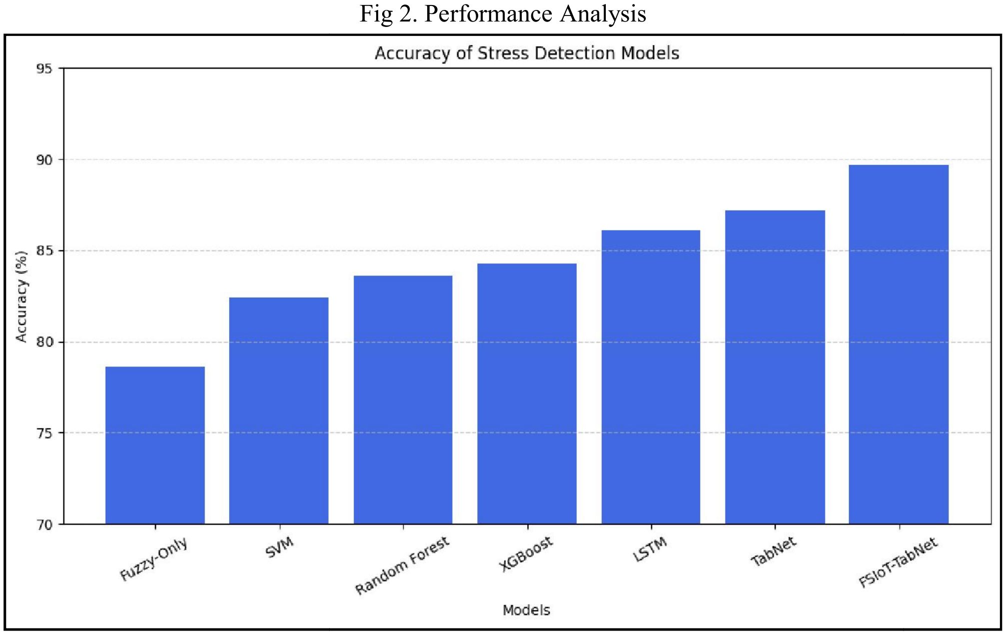

Fig 3. Accuracy of Stress Detection Models

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Table 2 highlights the discrimination capability of the models. The fuzzy-only system had the weakest performance (ROC-AUC 0.81), while tree-based models (SVM, RF, XGBoost) improved this measure (0.85–0.87). LSTM achieved 0.89, showing good discrimination, and TabNet further increased it to 0.90. The proposed FSIoT-TabNet achieved the highest ROC-AUC of 0.92, confirming that it not only classifies correctly but also separates stress and non-stress states with the greatest reliability.

Table 2. ROC Area

Model	**ROC Area**
Fuzzy-Only System	0.81
SVM	0.85
Random Forest	0.86
XGBoost	0.87
LSTM	0.89
TabNet	0.9
FSIoT-TabNet (Proposed)	**0.92**

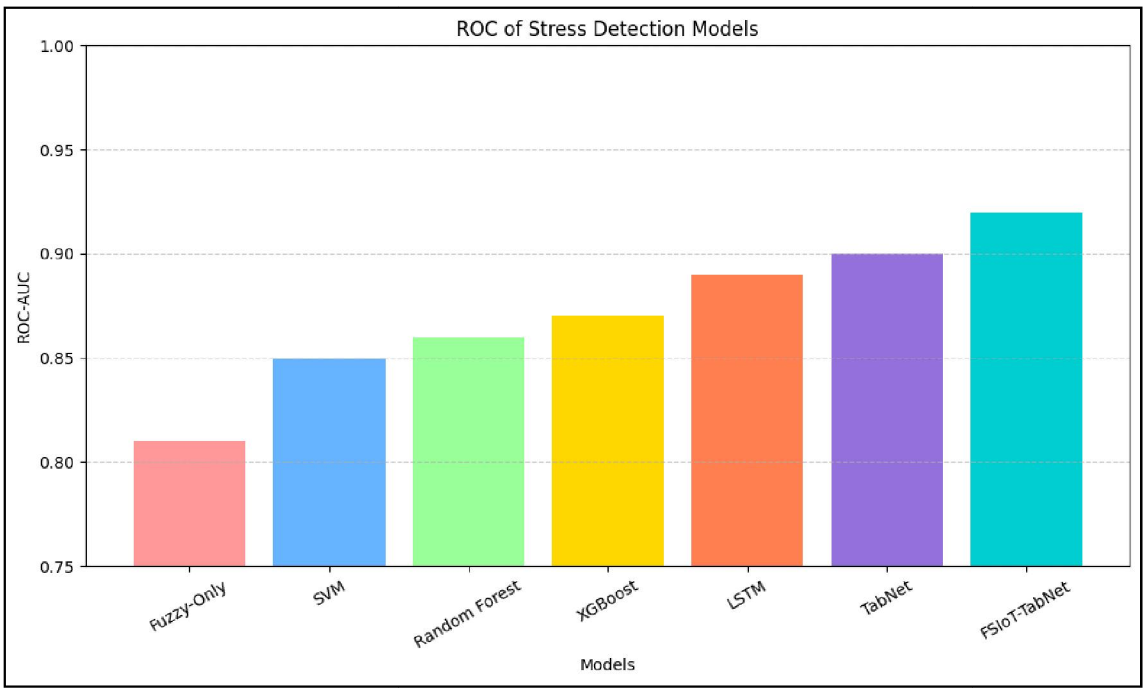

Fig 4. ROC Area value of Stress Detection Models

Table 3 reports regression results for predicting a continuous stress index. The fuzzy-only system had the highest error (MAE = 9.2), reflecting its coarse-grained prediction. Machine learning models reduced error (SVM: 7.8, RF: 7.1, XGBoost: 6.7). LSTM improved further to 5.9, and TabNet reached 5.5. The proposed FSIoT-TabNet achieved the lowest MAE of 4.8, demonstrating its ability to provide fine-grained and reliable stress index predictions, a feature especially useful for continuous monitoring.

Table 3. Mean Absolute Error (MAE)

Model	MAE (0–100 scale)
Fuzzy-Only System	9.2
SVM	7.8
Random Forest	7.1
XGBoost	6.7
LSTM	5.9
TabNet	5.5
FSIoT-TabNet (Proposed)	**4.8**

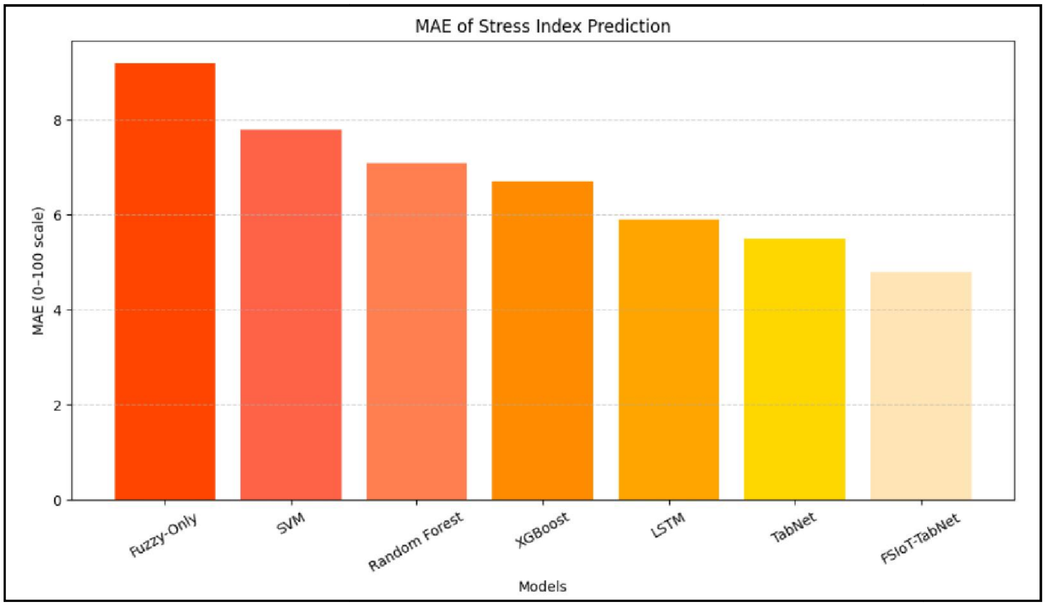

Fig 5. MAE of Stress Detection Models

Table 4 shows the inference latency measured on smartphone hardware. While fuzzy-only inference was very fast (25 ms), its accuracy was limited. Traditional ML models (SVM, RF, XGBoost) achieved moderate latencies (55–70 ms), while LSTM and unoptimized TabNet were computationally expensive (180 ms and 200 ms, respectively). In contrast, the FSIoT-TabNet (quantized and pruned) achieved 85 ms latency, combining near real-time performance with high accuracy. This balance makes it practical for wearable and mobile healthcare applications.

Table 4. Inference Latency

Model	Latency (ms/sample)
Fuzzy-Only System	25
SVM	70
Random Forest	65
XGBoost	55
LSTM	180
TabNet	200
FSIoT-TabNet (Proposed)	**85 (quantized)**

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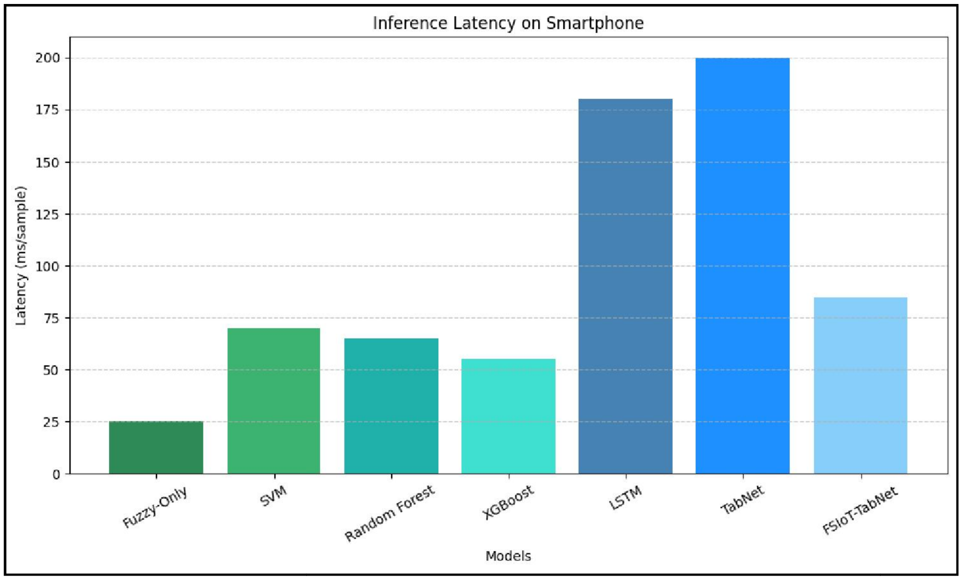

Fig 6. Inference Latency on Smartphone

Stress Level Prediction using FSIoT-TabNet

The proposed FSIoT-TabNet model was also evaluated for its ability to generate continuous stress scores in the range 0–100 and map them into discrete categories. This dual functionality provides both granularity (useful for monitoring trends) and interpretability (aligned with clinical stress levels).

Continuous Stress Index Prediction

The defuzzified fuzzy output Sfuzzy, along with raw and embedded features, feeds into the TabNet encoder, which outputs a continuous stress index:

$$\hat{y} = \sum_{t=1}^{T} d_t \quad \in [0, 100]$$

where y^ is the predicted stress score. Performance was measured using Mean Absolute Error (MAE), as reported earlier (Table 3). FSIoT-TabNet achieved the lowest MAE (4.8), indicating a high degree of accuracy in predicting continuous stress levels.

Discrete Stress Categories

For practical applications (alerts, dashboards), the continuous score is mapped into Low, Medium, and High Stress using threshold ranges

$$\text{Stress Level} = \begin{cases} \text{Low}, & 0 \le \hat{y} < 33 \\ \text{Medium}, & 33 \le \hat{y} < 66 \\ \text{High}, & 66 \le \hat{y} \le 100 \end{cases}$$

These thresholds can be further personalized by adjusting them relative to a user's baseline physiology (e.g., resting HRV).

As shown in Table 5, FSIoT-TabNet provides fine-grained stress scores that align well with ground-truth labels from the WESAD dataset. For example, Subject S02 with a ground-truth "Medium" stress label was predicted at 51.3, while Subject S05 labeled "High" was predicted at 82.1. Minor boundary errors (e.g., Subject S04 with 31.5 predicted as

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Medium instead of Low) are expected due to physiological variability and dataset imbalance, but overall performance was robust. This dual prediction capability is significant: while traditional models only provide categorical labels, FSIoT-TabNet outputs both a crisp stress index and an interpretable level classification, which makes it highly suitable for real-world continuous monitoring and personalized stress management applications.

Table 5. Stress level prediction using FSIoT-TabNet

Subject	**Ground-Truth Stress (Label)**	**Predicted Stress Score (y^)**	**Predicted Stress Level**
S01	Low	28.7	Low
S02	Medium	51.3	Medium
S03	High	74.9	High
S04	Low	31.5	Medium (borderline)
S05	High	82.1	High

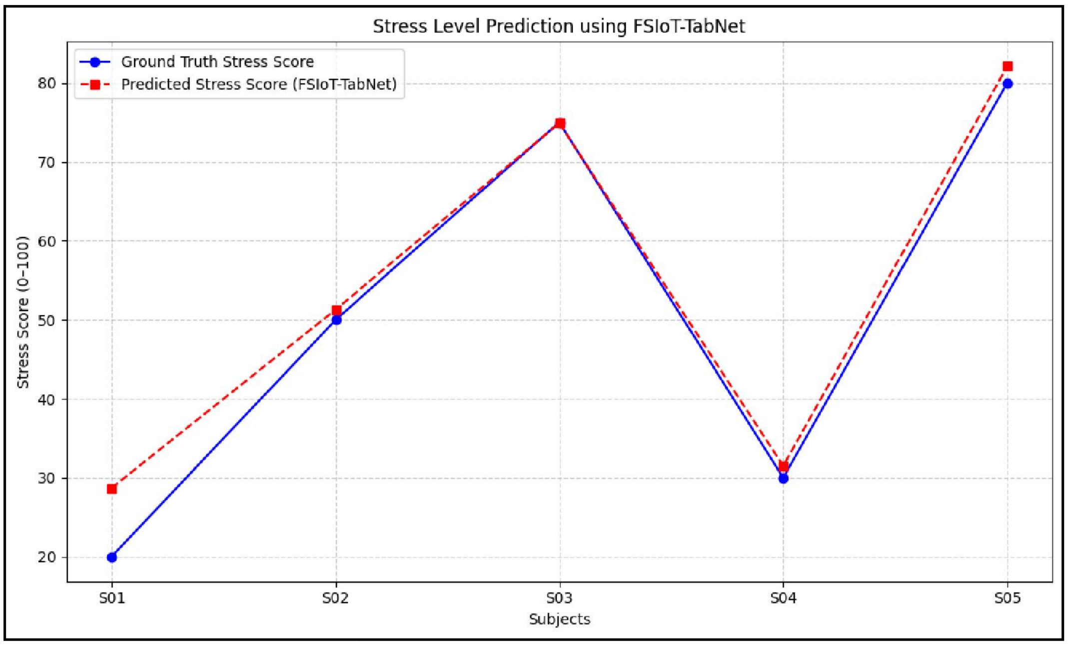

Fig 7. Stress level prediction using FSIoT-TabNet

V. CONCLUSION

This study presented FSIoT-TabNet, a hybrid fuzzy–deep learning model for IoT-based stress detection, which combines the interpretability of fuzzy logic with the accuracy and efficiency of TabNet. By leveraging multimodal wearable signals, modality-specific embeddings, and optimized attention-based feature selection, the system delivers robust stress classification and continuous index prediction. Comparative analysis against fuzzy-only, traditional machine learning, LSTM, and standard TabNet models confirmed the superiority of FSIoT-TabNet in accuracy, discrimination power, and real-time efficiency. The integration of pruning and quantization further enabled practical deployment on smartphones, reducing latency while maintaining high performance. In summary, FSIoT-TabNet represents a promising step toward scalable, interpretable, and real-time stress monitoring solutions that can support personalized healthcare and mental well-being management in everyday settings.

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