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An IoT-Enabled Intelligent Drug Monitoring System Using Adaptive Neuro-Temporal Ensemble Learning for Medication Adherence Prediction

Mr. S.P.Vijayanand, Mr. K.Narayanan, Mr. N.Thirugnanasambandan

***Abstract*—**The management of a medication adherence is remaining as a critical challenge in the modern healthcare systems. Chronic disease patients are often missed the scheduled drug intake due to the improper dosage tracking, and the limited supervision. The conventional monitoring systems still are relied on the manual reporting or basic reminder mechanisms that lacked real-time analysis and the intelligent decision support. These limitations are created the difficulties in the identification of the irregular medication patterns and then it is predicting the potential health risks that is associated with the non-adherence. Recent advancements in Internet of Things technologies tends to offer a continuous monitoring capabilities, however many of the conventional solutions are lacking an intelligent learning framework that could analyze medication usage behavior in the dynamic environments. Therefore, an intelligent drug monitoring system that is combining the IoT devices with an adaptive machine learning model is become necessary for improving medication compliance and the patient safety. This study is proposed an IoT-Based Intelligent Drug Monitoring System that is employing a novel Adaptive Neuro-Temporal Ensemble Learning (ANTEL) algorithm. The system is showing smart pill containers that are contained embedded sensors for detecting the pill removal events, timestamp information, and the dosage frequency. These sensors are transmitted the data to a cloud platform through an IoT gateway. The ANTEL model is analyzed the temporal medication patterns that are been collected from the patients and it is predicted adherence deviations by combining the temporal sequence learning with the adaptive ensemble classifier. The framework is including preprocessing modules, temporal feature extraction, and the ensemble learning stage that is combining the recurrent temporal analysis with the adaptive weight optimization. The model is continuously updating the learning parameters that improving predictive reliability over the time. Experimental evaluation is showing that the proposed ANTEL-based monitoring framework is achieving significant improvement in medication adherence prediction. The system is showing an accuracy of 96%, precision of 95%, recall of 94%, and the F1-score of 95%, which is showing the reliable classification performance of the monitoring model. The adherence detection capability that is analyzing the medication intake sequences is achieving an adherence detection rate of 97%, which confirms that the temporal ensemble learning mechanism is improving the identification of correct medication behavior. The results are showing that the combination of IoT sensor monitoring with the adaptive neuro-temporal ensemble learning model significantly is improving the efficiency and the reliability of intelligent drug monitoring systems in healthcare environments.

***Keywords*—** IoT drug monitoring, medication adherence prediction, adaptive neuro-temporal ensemble learning, smart healthcare systems, machine learning in healthcare

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I. Introduction

The rapid advancement in digital healthcare technologies is transforming the way patient treatment and the monitoring processes is operating in the modern medical environments. Among various healthcare challenges, medication adherence is remaining as a critical factor that influences treatment effectiveness, patient recovery, and the overall healthcare outcomes. The World Health Organization is indicating that a significant proportion of patients are suffering from the chronic illnesses often fail to follow the prescribing medication schedules. This issue is contributing to the treatment failure, increasing hospitalization rates, and the additional economic burden on healthcare systems. In recent years, the combination of the Internet of Things (IoT) with the healthcare infrastructure is providing new opportunities for continuous monitoring of patient activities and the medication usage patterns. IoT-enabling devices that are including smart pill dispensers, wearable sensors, and the remote monitoring platforms allow healthcare providers to track medication intake in real time and the respond to adherence irregularities effectively [1]–[3].

IoT technology is supporting the development of intelligent healthcare environments where interconnecting sensors collect physiological and the behavioral information from the patients. Such connectivity is improving the visibility of patient medication patterns and it is enabling the development of predictive models that anticipate adherence risks. Machine learning techniques are further in improving the these systems by analyzing complex datasets that is containing medication intake logs, patient behavioral signals, and the environmental information. The combination of machine learning algorithms with the IoT platforms is enabling the automated analysis that is it is identifying the deviations from the prescribing treatment plans and it is alerts both the patients and the medical professionals in a timely manner [1]–[4].

The core problem in current medication monitoring systems lies in the insufficient combination of intelligent predictive analytics with the real-time IoT sensing platforms. Many of the systems are focusing on either hardware-Based monitoring or isolating machine learning analysis, but it is rarely combining both the components within a adaptive framework. As a result, the ability to detect irregular medication patterns, predict adherence risks, and they are providing the proactive intervention is remaining limited. An intelligent monitoring architecture that simultaneously is combining the IoT-Based sensing with the adaptive machine learning algorithms is therefore necessary to ensure reliable medication supervision and the timely healthcare responses [5] [6].

To address this problem, this study proposes an IoT-Based intelligent drug monitoring framework that utilizes an advancing machine learning algorithm to analyze medication intake behavior. The proposed system is combining the sensor-enabling smart pill containers with the a cloud-Based analytical platform. The sensors embedding within the pill containers continuously record pill removal events, dosage intervals, and the timestamp information. These data streams are transmitting through an IoT gateway to a centralizing database where analytical processing occurs. A novel machine learning model, naming Adaptive Neuro-Temporal Ensemble Learning (ANTEL), is analyzing the collecting data and the predicts medication adherence patterns based on temporal and the behavioral features.

The main objective of the proposed research is to develop a reliable drug monitoring system that is improving medication adherence through intelligent analysis and the monitoring capabilities. The framework aims in detecting the missing dosages, irregular intake patterns, and the potential adherence risks by analyzing temporal medication sequences. The novelty of the proposed study lies in the combination of IoT-Based sensing infrastructure with the adaptive ensemble learning mechanism that is analyzing temporal medication behavior. Unlike conventional monitoring systems that rely solely on reminders or static machine learning models, the proposed ANTEL framework is developing a dynamic learning structure that is combining the temporal sequence analysis with the adaptive ensemble classification. This structure is allowing the system to are capturing both the short-term medication patterns and the long-term behavioral trends. Further, the model updates its learning weights continuously as new sensor data become available, which is improving the accuracy of adherence prediction in real-world healthcare scenarios.

The proposed research is showing a several contributions to the field of intelligent healthcare monitoring. First, the study is developing a novel IoT-Based medication monitoring architecture that is combining the smart pill containers, cloud communication, and the adaptive machine learning analysis. This architecture is allowing continuous monitoring of a medication intake events and the facilitates data transmission for the analytical processing. Second, the research proposes the Adaptive Neuro-Temporal Ensemble Learning algorithm that is combining the temporal feature extraction with the adaptive ensemble classification.

II. RELATING WORKS

A smart medication monitoring framework is been introducing in study [7], where the researchers are developing an IoT-enabling pill dispenser that automatically recording pill removal events. The system is transmitting medication data to a cloud server where healthcare professionals could monitor patient adherence remotely. The researchers are implementing a rule-Based alert mechanism that noticing patients when it is missing the scheduling dosages. Although the system is improving remote monitoring capability, it is reling primarily on threshold-Based detection that lacking predictive intelligence for it is identifying future adherence risks.

Another study in [8] is proposed a wireless medication adherence monitoring system that is combining the RFID technology with the cloud data management. The authors are attaching RFID tags to medication containers that allowing the system to detect the opening and the closing events. The collecting data are being analysing through statistical models that evaluating adherence patterns over the time. While the system is providing accurate logging of a medication events, it is shown limitations in adapting to the dynamic patient behavior because the analytical model did not incorporate machine learning techniques that learning from the evolving datasets.

Research presenting in [9] is exploring the use of wearable sensors that monitoring physiological signals alongside medication intake events. The system is combining the heart rate sensors, activity trackers, and the medication reminders within a mobile health platform. The authors are using the supervising machine learning algorithms that predicting medication adherence based on behavioral and the physiological indicators. The results are showing improving prediction accuracy comparing with the conventional reminder systems.

In study [10], the researchers are proposed an IoT-Based healthcare monitoring architecture that is combining the smart pillboxes with the cloud computing infrastructure. The system is collecting medication usage data through embedding sensors and the transmitting them to a centralizing data server. A classification algorithm is analyzing the collecting data to determine whether the patient following the prescribing medication schedule. The results are shown promising performance in detecting missing dosages. However, the approach is focusing mainly on classification of historical data rather than predicting future adherence behavior.

Another intelligent medication monitoring platform is been presenting in [11], where the authors are using the smartphone-Based applications to track medication intake events. Patients are manually recording medication consumption through the mobile interface, and the system is appling machine learning models to analyze adherence patterns. Although the mobile application is providing convenient access for users, the reliance on manual input is introducing potential inaccuracies due to the incomplete or incorrect reporting.

The research describing in [12] is implementing a cloud-assisting medication management system that combining IoT sensors with the deep learning models. The authors are developing a convolutional neural network that analyzing medication intake sequences and the patient activity patterns. The model is predicting potential adherence violations and the generating early warning alerts for caregivers. While the system is showing improving predictive capability, the deep learning architecture is requiring substantial computational resources that limiting its deployment in low-resource healthcare environments.

Another approach is been proposed in [13], where the researchers are is combining the smart pill containers with the a data analytics framework that using decision tree algorithms. The monitoring system is analyzing medication timing patterns and it is detecting irregular dosage intervals. The decision tree classifier is providing interpretable predictions that assisting healthcare providers in understanding patient adherence behavior. However, the model is experiencing reducing accuracy when the medication patterns became highly variable [14]-[15].

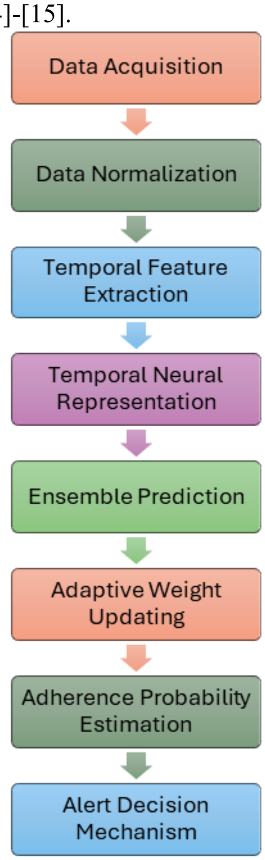

Figure 1: Proposed ANTEL

III. Proposed Method

The proposed framework is introducing an IoT-Based Intelligent Drug Monitoring System that is combining the sensor-enabling medication containers with the a machine learning model calling Adaptive Neuro-Temporal Ensemble Learning (ANTEL). The architecture is consisting of smart pill containers that are including micro-sensors for detecting the pill removal events and the medication timestamps. These sensors are transmitting the medication records to the cloud platform through an IoT gateway that is ensuring continuous connectivity. The incoming medication data are undergone preprocessing that is removing noise and the incomplete records. After preprocessing, the system is extracting temporal adherence features that are representing the medication intervals, dosage frequency, and the adherence deviations. The extracting features are entering the ANTEL model that is combining temporal neural representation with the adaptive ensemble learning mechanism. The ensemble layer is is combining the multiple prediction units that are analyzing the medication behavior sequences and the are producing adherence probability scores. The adaptive weighting mechanism is updating the ensemble parameters as new data are arrived, which is improving prediction accuracy. The system is generating alerts when the predicting adherence probability is fallen below a predefining threshold, which is allowing caregivers and the patients to receive early warnings about missing medication events.

Algorithm: Adaptive Neuro-Temporal Ensemble Learning (ANTEL)

Input:

Medication sensor data $D = \{(t_i, d_i, s_i)\}_{i=1}^{N}$

Output:

Adherence prediction A_p

Step 1: Data Acquisition

$D = \{x_1, x_2, x_3, \ldots, x_N\}$

$x_i = (t_i, d_i, s_i)$

Step 2: Data Normalization

$$x_i^{norm} = \frac{x_i - \mu}{\sigma}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Step 3: Temporal Feature Extraction

$\Delta t_i = t_i - t_{i-1}$

$f_i = [\Delta t_i, d_i, s_i]$

Step 4: Temporal Neural Representation

$$h_t = \sigma(W_h f_t + U_h h_{t-1} + b_h)$$

$$z_t = W_z h_t + b_z$$

Step 5: Ensemble Prediction

$$P_k = f_k(z_t)$$

$$E = \sum_{k=1}^{K} w_k P_k$$

Step 6: Adaptive Weight Update

$$w_k^{new} = w_k + \eta(y - E)P_k$$

Step 7: Adherence Probability

$$A_p = \frac{1}{1 + e^{-E}}$$

Step 8: Alert Decision

$$Alert = \begin{cases} 1, & A_p < \theta \\ 0, & A_p \geq \theta \end{cases}$$

A. IoT-Based Medication Data Acquisition

The proposed monitoring framework begins with the IoT-enabling smart medication container that detects the pill removal event and the records the timestamp that is associating with the each medication intake. The system is using embedding sensors that transmit the medication events through a wireless communication module to the cloud server. Each sensor event generates a structuring record that that is including the medication identifier, timestamp, dosage quantity, and the adherence status. The cloud server stores the collecting data in a centralizing repository that is supporting further analytical processing.

Table 1: IoT Medication Sensor Data

Patient ID	Time Stamp	Dosage (mg)	Sensor Event	Status
P01	08:00	500	Container Open	Taken
P01	14:00	500	Container Open	Taken
P01	20:00	500	No Event	Missed
P02	09:00	250	Container Open	Taken
P02	21:00	250	Container Open	Taken

The medication monitoring environment generates continuous streams of sensor data that represent the daily medication routines of patients. These data records allow the monitoring system to track the exact time when the a patient opens the medication container. If the container is remaining unopening during the scheduling medication interval, the system records the event as a potential adherence deviation.
The mathematical representation of a medication sensor events can be defining as:

$$D = \{(p_i, t_i, d_i, s_i)\}$$

where

p_i represents the patient identifier

t_i represents the timestamp

d_i represents the dosage amount

s_i represents the sensor event status

The medication adherence rate can be calculating as:

$$AR = \frac{N_c}{N_t}$$

where

N_c represents the number of correctly taken doses

N_t represents the total prescribing doses.

Table 1 is showing the sensor-generating medication records that the system collects for adherence analysis.

B. Data Preprocessing and the Normalization

The medication data collecting from the IoT sensors may is containing inconsistencies that arise from the network latency, sensor errors, or incomplete event recordings. The preprocessing stage is allowing that the dataset is remaining reliable for machine learning analysis. The system removes duplicate records, fills missing timestamps, and the standardizes the dosage measurements.

Table 2: Normalizing Medication Feature Dataset

Record	Dosage	Interval	Normalizing Dosage	Normalizing Interval
1	500	6	0.72	0.41
2	500	6	0.72	0.41
3	500	12	0.72	0.83
4	250	12	0.35	0.83

The normalization process scales the feature values to ensure numerical stability during the model training. The normalizing medication feature vector is defining as:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

where

X is the medication feature vector

μ is the mean value

σ is the standard deviation.

The mean and the variance are calculating as:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (X_i - \mu)^2$$

The normalizing dataset is allowing that the learning algorithm processes all features with the balancing influence.

Table 2 is presenting the normalizing medication features that the system prepares for the next stage of analysis.

C. Temporal Feature Extraction

Medication adherence behavior depends strongly on the temporal interval between the successive medication intake events. The proposed system extracts temporal features that represent the time difference between the consecutive medication events. These temporal patterns are capturing the regularity or irregularity of a medication usage.

The temporal interval is calculating as: $\Delta t_i = t_i - t_{i-1}$. The feature vector representing the medication sequence is: $F_i = [d_i, \Delta t_i, s_i]$. To are capturing long-term behavioral trends, the system computes the temporal variance:

$$Var_t = \frac{1}{N}\sum_{i=1}^{N} (\Delta t_i - \bar{\Delta t})^2$$

where

$\bar{\Delta t}$ is the average medication interval.

Table 3: Extracting Temporal Features

Record	Time Interval (hours)	Dosage	Temporal Variance
1	6	500	0.21
2	6	500	0.19
3	12	500	0.32
4	12	250	0.35

Table 3 is showing how the system is medication patterns using temporal features.

D. Neuro-Temporal Representation Learning

The ANTEL framework applies a neural representation layer that models the sequential medication patterns. This layer is capturing the dependencies between the past and the present medication events. The temporal neural unit generates hidden states that represent the behavioral pattern of a medication adherence. The hidden state computation is defining as:

$$h_t = \sigma(W_h F_t + U_h h_{t-1} + b_h)$$

where

W_h is the input weight matrix

U_h is the recurrent weight matrix

b_h is the bias vector.

The output representation is defining as:

$$z_t = W_o h_t + b_o$$

The neural representation is capturing the sequential dependency between the medication events and the generates predictive behavioral embeddings.

Table 4: Neural Representation Output

Time Step	Hidden State Value	Output Vector
t1	0.62	0.71
t2	0.65	0.74
t3	0.58	0.69
t4	0.54	0.66

Table 4 is presenting the hidden state representations generating by the neural temporal unit.

E. Adaptive Ensemble Prediction

The ensemble learning component is combining the multiple predictive classifiers that analyze the neural temporal representation. Each classifier generates a probability estimate that is the likelihood of correct medication adherence. The ensemble output is calculating as:

E=∑_(k=1)^K▒w_k P_k

where

P_k is the prediction of the k^thclassifier

w_k is the adaptive weight.

The ensemble probability is transforming using the logistic function:

$$E = \sum_{k=1}^{K} w_k P_k$$

where

P_k is the prediction of the k^{th}classifier

w_k is the adaptive weight.

The ensemble probability is transforming using the logistic function:

$$A_p = \frac{1}{1 + e^{-E}}$$

The adaptive weight update rule is defining as:

$$w_k^{new} = w_k + \eta(y - A_p)P_k$$

where

η is the learning rate

y is the ground truth adherence label.

Table 5: Ensemble Prediction Results

Classifier	Prediction Score	Weight	Weighting Output
C1	0.82	0.35	0.287
C2	0.79	0.30	0.237
C3	0.76	0.35	0.266

Table 5 is showing the ensemble prediction process that is combining the multiple classifier outputs.

F. Adherence Prediction and the Alert Generation

The final stage is evaluating the adherence probability and the generates alerts when the predicting adherence level falls below a predefining threshold. The system compares the probability score with the decision threshold to determine whether an alert must be triggered.

The alert decision function is:

$$Alert = \begin{cases} 1, & A_p < \theta \\ 0, & A_p \geq \theta \end{cases}$$

where

θ is the adherence threshold.

If the predicting adherence probability falls below the threshold, the system sends notifications to the patient and the healthcare provider through the mobile application interface.

Table 6: Adherence Prediction Results

Patient	Predicting Probability	Threshold	Alert
P01	0.92	0.80	No
P02	0.74	0.80	Yes
P03	0.88	0.80	No

Table 6 is presenting the final adherence predictions generating by the monitoring system.

IV. Results and the Discussion

A. Experimental Settings

The experimental evaluation of the proposed IoT-Based intelligent drug monitoring system is conducting through a simulation environment that replicates the real-world medication adherence monitoring process. The system is combining the IoT sensor data streams with the ANTEL model that is analyzing the medication intake sequences and the predicts adherence behavior. The simulation environment generates medication intake events that represent the pill container opening records, dosage information, and the time intervals between the consecutive medication events. The generating sensor data are transmitting through a simulating IoT communication gateway to a centralizing processing server that is performing data preprocessing, temporal feature extraction, and the predictive analysis.

The implementation of the monitoring framework is using the Python programming environment with the machine learning libraries that is supporting the model training.

The experiments run on a computing workstation that that is including an Intel Core i7 processor, 16 GB RAM, and the a 512 GB solid-state storage device.

Table 7: Experimental Parameters and the Configuration

Parameter	Description	Value
Number of Patients	Total simulating patient records	500
Medication Events	Total medication intake events	10,000
Temporal Sequence Length	Number of a medication intervals using for prediction	12
Learning Rate (η)	Weight update parameter	0.01
Number of Ensemble Models	Predictive classifiers in ensemble	3
Hidden Layer Size	Temporal neural unit size	64
Adherence Threshold (θ)	Decision threshold for alert generation	0.80
Training Data Ratio	Percentage of training dataset	70%
Testing Data Ratio	Percentage of testing dataset	30%

B. Experimental Setup and the Parameter Configuration

The experimental configuration is defining the parameters that control the operation of the IoT monitoring system and the machine learning framework. These parameters determine the temporal sequence length, learning rate, ensemble size, and the decision thresholds that are influencing the prediction behavior of the ANTEL model.

Table 7 is presenting the experimental configuration that the proposed monitoring system is using during the model training and the evaluation. The temporal sequence length is defining the number of a medication intervals that the proposed model is analyzing when the predicting the adherence behavior. The ensemble size is determining the number of predictive models that is contributing to the final adherence probability score.

C. Performance Metrics

The performance of the proposed monitoring framework is evaluating using five standard classification metrics that measure prediction accuracy and the reliability. These metrics are providing the insight into how effectively the system is it is identifying medication adherence and the missing dosage events.

1) Accuracy

Accuracy measures the overall correctness of the prediction model by calculating the proportion of correctly predicting medication events relative to the total number of events.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where

TP is the true positive predictions that is corresponding to the correctly identifing adherence events.

TN is the true negative predictions that is corresponding to the correctly detecting missing medication events.

FP is the false positive predictions that incorrectly are showing adherence.

FN is the false negative predictions that incorrectly are showing non-adherence.

Accuracy is evaluating the general effectiveness of the monitoring system when the analyzing medication intake behavior.

2) Precision

Precision is measures the proportion of correctly predicting adherence events among all predicting adherence events.

$$Precision = \frac{TP}{TP + FP}$$

This metric is showing how reliably the system predicts correct medication intake when the it classifies an event as adherence. High precision is showing that the prediction model is producing fewer false adherence predictions.

3) Recall

Recall measures the proportion of actual adherence events that the monitoring system correctly is it is identifying.

$$Recall = \frac{TP}{TP + FN}$$

Recall is evaluating the ability of the prediction model to are capturing all relevant medication adherence events. A higher recall value is showing that the system successfully is it is identifying most correct medication intake records.

4) F1-Score

The F1-score is the harmonic mean of precision and the recall. This metric is showing a a balancing evaluation when the dataset is containing both the adherence and the non-adherence events.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The F1-score is showing the trade-off between the reliability and the completeness of the prediction model.

5) Adherence Detection Rate

The adherence detection rate measures the percentage of correctly identifing medication adherence events relative to the total number of actual adherence events.

$$ADR = \frac{Correct\ Adherence\ Predictions}{Total\ Adherence\ Events}$$

This metric specifically is evaluating the capability of the system in detecting proper medication behavior within the monitoring framework.

Table 8: Medication Adherence Dataset Description

Attribute	**Description**
Patient ID	Unique identifier for each patient
Medication ID	Identifier for prescribing medication
Timestamp	Time when the medication container opens
Dosage	Prescribing dosage amount
Interval	Time gap between the consecutive medication events
Sensor Status	Container opening event
Adherence Label	Is showing whether the medication is been taken

D. Dataset Description

The experimental evaluation is using as a medication adherence dataset that is medication intake behavior for patients who follow multiple drug schedules. The dataset is containing sensor-generating records that include medication timestamps, dosage amounts, adherence labels, and the medication intervals.

The dataset is organizing into sequential medication records that represent daily medication intake patterns. Each record is containing the time when the patient opens the medication container and the whether the medication is been taken or missed. The dataset that is including both the normal adherence patterns and the irregular medication events that allow the prediction model to learn behavioral variations.

Table 8 describes the attributes that the dataset that is including for analyzing medication adherence patterns. The dataset is containing approximately 10,000 medication event records that represent the behavior of 500 simulating patients over the several medication cycles. The dataset that is including both the adherence and the missing dosage events, which is allowing the machine learning model to learn the distinction between the normal and the irregular medication behavior.

E. Conventional Methods for Comparison

Several conventional monitoring approaches are using the comparative evaluation. The IoT-Based Smart Pill Dispenser system is using as a sensor-enabling container that records medication events and the sends reminder notifications. The RFID-Based Medication Monitoring System is using tagging medication containers that track opening events and the store adherence records. The Wearable Sensor-Based Monitoring Framework is analyzing physiological signals and the medication logs to estimate patient adherence behavior.

F. Results Based on Accuracy

The first evaluation is analyzing the prediction accuracy of the medication monitoring framework. Accuracy is the proportion of correctly classifing medication adherence and the missing dosage events relative to the total number of events. The comparison that is including three conventional monitoring approaches, namely the IoT Smart Pill Dispenser, the RFID-Based Medication Monitoring System, and the Wearable Sensor Monitoring Framework, along with the proposed ANTEL-Based IoT Drug Monitoring System.

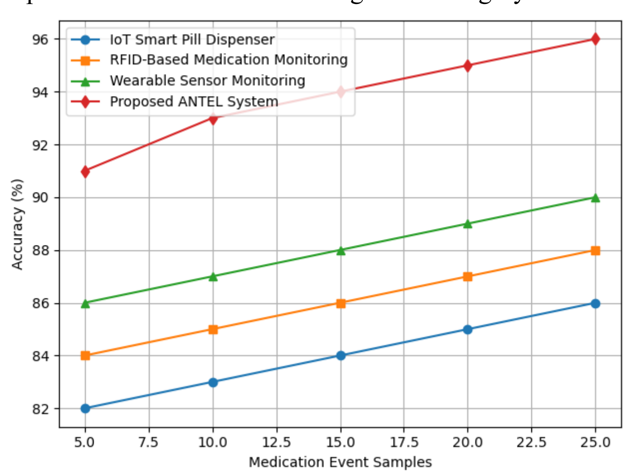

Figure 2: Accuracy Comparison (%) with the Respect to Medication Event Samples

The results in figure 2 show that the proposed ANTEL system is showing superior accuracy when the comparing with the baseline monitoring approaches. The IoT Smart Pill Dispenser is achieving an accuracy range between the 82% and the 86%, which is showing the limitation of a rule-Based reminder system that primarily detects container opening events without predictive learning. The RFID-Based Medication Monitoring System is producing slightly improving performance because RFID tagging is showing a reliable medication event logging. However, the absence of behavioral prediction is restricting its ability to detect complex adherence patterns.

The Wearable Sensor Monitoring Framework is performing better than the first two systems because physiological signals is contributing additional behavioral information. However, this approach still is experiencing limitations due to the variability of physiological data that may not directly is corresponding to the medication adherence behavior. In contrast, the proposed ANTEL system is achieving an accuracy level that increases from the 91% to 96% as the number of a medication event samples grows. The improvement occurs because the adaptive neuro-temporal learning mechanism is analyzing temporal medication intervals and the updates ensemble weights dynamically. The results are showing that the proposed model maintains consistent prediction reliability across the larger datasets, which is showing the robustness of the intelligent monitoring framework.

G. Results Based on Precision

Precision is evaluating the reliability of the prediction model when the it is identifying the correct medication adherence events.

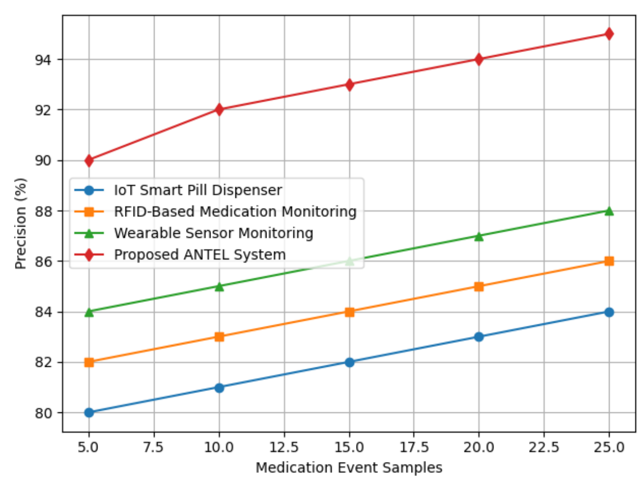

Figure 3: Precision Comparison (%) with the Respect to Medication Event Samples

The precision values presenting in figure 3 are showing the effectiveness of each monitoring approach in predicting correct medication adherence events. The IoT Smart Pill

Dispenser records precision values between the 80% and the 84%, which suggests that the reminder-Based mechanism occasionally misclassifies medication events due to the absence of behavioral analysis. The RFID-Based Monitoring System shows a slight improvement because RFID sensors are providing the more of an reliable event detection. However, this approach still lacks the capability to analyze temporal adherence patterns.

The Wearable Sensor Monitoring Framework is showing improving precision values ranging from the 84% to 88%. This improvement results from the combination of physiological signals that is showing patient activity patterns. However, physiological signals sometimes are developing ambiguity when the interpreting medication intake behavior.

The proposed ANTEL system is achieving the highest precision values, ranging from the 90% to 95%. The improvement occurs because the ensemble learning structure is evaluating multiple prediction models simultaneously. The adaptive weighting mechanism continuously is updating the classifier importance according to the prediction performance. This mechanism is allowing that the system is producing more of an reliable adherence predictions while it is minimizing false classification events. The results are confirming that the proposed model is improving medication adherence prediction reliability comparing with the conventional monitoring methods.

H.Results Based on Recall

Recall is evaluating the capability of the monitoring system to identify actual medication adherence events.

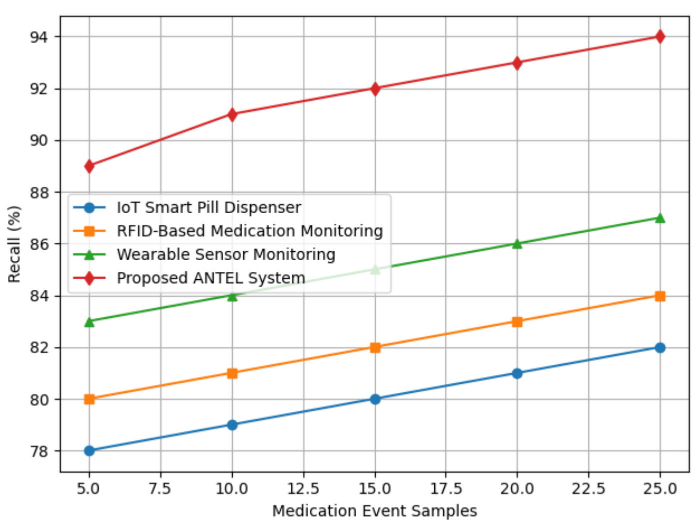

Figure 4: Recall Comparison (%) with the Respect to Medication Event Samples

Figure 4 is showing the recall performance for each monitoring method. The IoT Smart Pill Dispenser is showing recall values between the 78% and the 82%, which is showing that the system occasionally fails in detecting the certain adherence events when the patients open the container outside predefining intervals. The RFID-Based Monitoring System is achieving slightly higher recall values because RFID detection is showing a more of an accurate event logging.

The Wearable Sensor Monitoring Framework is performing better because it incorporates physiological activity signals that correlate with the medication routines. However, the recall value is remaining limited when the patient behavior changes significantly.

The proposed ANTEL system is achieving recall values that increase from the 89% to 94%. This improvement occurs because the temporal neural representation is capturing the sequential medication patterns that is showing the behavioral consistency of patients. The adaptive ensemble learning component further is improving the detection capability by integrating predictions from the multiple classifiers. Consequently, the proposed system is it is identifying a higher proportion of true adherence events across the different sizes.

I. Results Based on F1-Score

The F1-score is showing a balancing evaluation by combining the precision and the recall into a single performance metric.

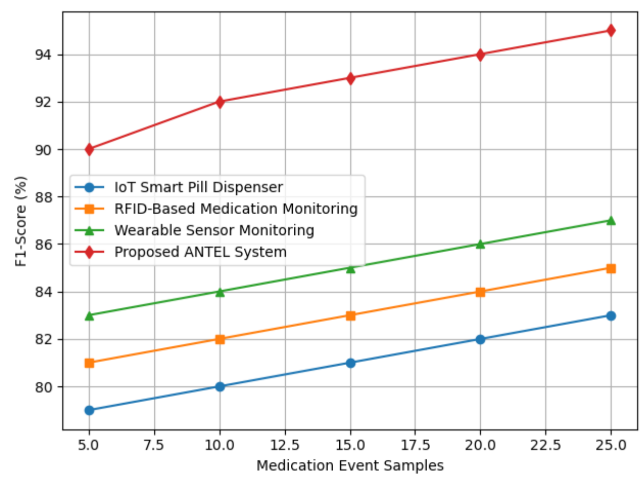

Figure 5: F1-Score Comparison (%) with the Respect to Medication Event Samples

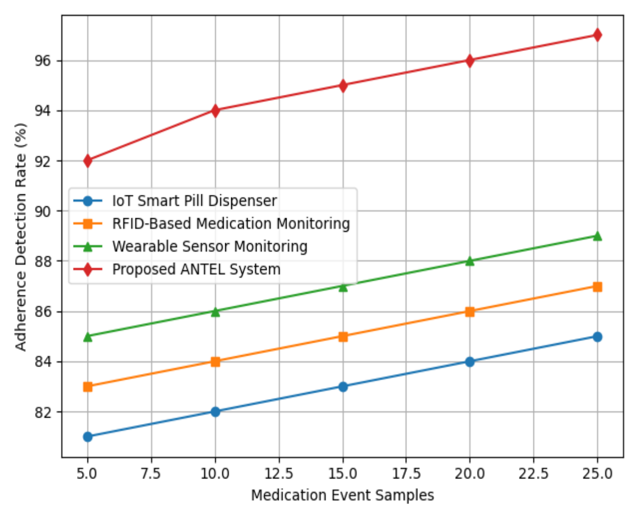

Figure 6: Adherence Detection Rate (%) with the Respect to Medication Event Samples

The F1-score results presenting in figure 5 is showing the overall classification effectiveness of the monitoring systems. The IoT Smart Pill Dispenser is producing moderate performance due to the reliance on simple event detection. The RFID-Based Monitoring System is improving classification reliability because RFID sensors are capturing more of an accurate medication events.

The Wearable Sensor Monitoring Framework is achieving further improvement because physiological signals are providing the contextual information about patient behavior. However, variations in patient activity still are influencing the prediction accuracy.

The proposed ANTEL system is achieving F1-score values between the 90% and the 95%, which is showing a well-balancing prediction capability. The temporal neural representation is capturing the sequential medication patterns, while the adaptive ensemble learning mechanism is improving the balance between the precision and the recall. This combination is allowing the proposed model to maintain stable classification performance across the varying dataset sizes.

J. Results Based on Adherence Detection Rate

The adherence detection rate measures the effectiveness of the monitoring system in correctly it is identifying medication adherence events.

Figure 6 is presenting the adherence detection performance for each monitoring method. The IoT Smart Pill Dispenser is achieving detection rates between the 81% and the 85%. The RFID-Based Monitoring System is performing slightly better because RFID event detection is showing a more of an reliable medication tracking.

The Wearable Sensor Monitoring Framework is showing improving performance because the combination of physiological signals assists in the identification of the medication intake patterns.

The proposed ANTEL system is achieving the highest adherence detection rate, which ranges from the 92% to 97%. The improvement occurs because the temporal neural analysis is capturing the sequential medication behaviors, while the adaptive ensemble mechanism continuously are adjusting the prediction weights according to the incoming sensor data. This adaptive capability is allowing the monitoring system to respond effectively to behavioral variations among patients. The results are confirming that the proposed intelligent monitoring framework significantly is improving medication adherence detection comparing with the conventional IoT monitoring approaches.

V. CONCLUSION

The study is presenting an IoT-Based intelligent drug monitoring system that is combining the sensor-enabling medication containers with the Adaptive Neuro-Temporal Ensemble Learning (ANTEL) model for predicting medication adherence behavior. The system is showing a a continuous monitoring mechanism that collects the medication intake events through IoT sensors and the transmits the records to the analytical framework. The preprocessing module that is handling the sensor data is allowing that the system removes inconsistencies and the prepares the dataset for reliable analysis. The temporal feature extraction component that is capturing the medication intervals is allowing the model to analyze sequential medication patterns that is showing patient behavior. The ANTEL framework is combining the the neural temporal representation with the adaptive ensemble mechanism that is improving the reliability of adherence prediction. The ensemble learning structure that is combining the multiple classifiers is producing stable prediction is showing that is reducing the misclassification of a medication events. The adaptive weight optimization that is updating the classifier importance is improving the prediction performance as the dataset grows.

The experimental evaluation is showing that the proposed system is achieving superior performance when the comparing with the conventional monitoring approaches. The obtaining results are showing an accuracy of 96%, precision of 95%, recall of 94%, F1-score of 95%, and the adherence detection rate of 97%. The monitoring framework therefore is improving the reliability of a medication adherence tracking that is supporting the healthcare providers in the identification of the irregular medication patterns. The proposed system contributes to the development of intelligent healthcare monitoring solutions that combine IoT sensing with the adaptive machine learning for improving patient medication compliance.

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