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Design of IoT-Based Wearables for Health Care Prediction Using Normalized-Patch Gan Based Fruit Fly Optimization

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Abstract: Healthcare is a critical sector where timely and accurate predictions can save lives and improve the quality of care. Traditional healthcare systems often lack the ability to process vast amounts of patient data efficiently. To address this, IoT technology is harnessed for seamless data collection and integration, facilitating real-time updates to a central database. The challenge lies in harnessing this data effectively to predict health conditions. The diversity of patient data, including Medical IDs, pulse rates, medical reports, and symptoms, requires sophisticated algorithms to extract meaningful insights. Moreover, the accuracy and reliability of predictions are vital to ensure patient safety. This paper presents the design of an Internet of Things (IoT)-based healthcare prediction system utilizing the Normalized Patch Generative Adversarial Network (NP-GAN) based Fruit Fly Optimization (FFO) algorithm. The proposed system aims to predict health conditions based on patient data, including Medical ID, pulse rate, medical reports, and symptoms. Through seamless integration of IoT technologies and AI algorithms, the system enables real-time monitoring and predictive analysis, enhancing patient care and medical decision-making. The system collects patient data including Medical ID, pulse rate measurements, medical reports, and reported symptoms. IoT devices facilitate real-time data transmission to the central database. Raw data undergoes preprocessing, including normalization and sequence alignment. Textual medical reports are transformed into numerical vectors using techniques like word embeddings. Features such as pulse rate trends, symptom sequences, and medical report patterns are extracted from the preprocessed data, providing valuable insights for prediction using NP-GAN. The RCNN algorithm, combining recurrent and convolutional layers, is employed for its ability to capture temporal dependencies and spatial patterns in data. The network learns to associate pulse rate trends, symptoms, and medical information for accurate predictions. The RCNN model is trained using historical patient data and validated using FFO to optimize hyperparameters and prevent overfitting. Real-time patient data is continuously fed into the trained RCNN-FFO model, which predicts potential health issues. Alerts are generated for medical professionals if anomalies or concerning patterns are detected. The system performance is assessed using metrics like accuracy, precision, recall, and F1-score. Continuous feedback and retraining improve prediction accuracy over time.

Keywords: *Healthcare, IoT, RCNN Algorithm, Prediction, Pulse Rate, Medical ID*

1. Introduction

In recent years, the convergence of Internet of Things (IoT) technology, healthcare, and machine learning has heralded a transformative era in the provision of healthcare services. IoT wearables, characterized by their interconnectedness and data-sensing capabilities, have emerged as potent tools in monitoring and improving individual health [1]. Simultaneously, machine learning, with its capacity to decipher intricate patterns within data, has revolutionized healthcare by enhancing diagnostics, predicting disease trajectories, and personalizing treatment plans [2].

The proliferation of IoT wearables has redefined how healthcare data is collected and utilized. These unobtrusive, sensor-laden devices, ranging from smartwatches to fitness trackers, have empowered individuals to take charge of their well-being by continuously monitoring vital signs, physical activity, and even sleep patterns [3]. This shift from episodic healthcare to continuous, real-time monitoring not only offers a comprehensive view of an individual health but also opens up new opportunities for early intervention and prevention [4].

In parallel, machine learning algorithms have harnessed the deluge of healthcare data generated by IoT wearables, electronic health records, and medical imaging [5]. These algorithms have the capability to decipher intricate relationships between various health indicators, enabling healthcare providers to make more informed decisions [6]. Machine learning ability to predict disease risks, optimize treatment plans, and identify anomalies has not only improved patient outcomes but also reduced healthcare costs [7].

As we stand at the intersection of these three domains - IoT wearables, healthcare, and machine learning - we witness a convergence that holds immense promise [8]. The synergy between wearable device data-rich inputs, the analytical prowess of machine learning algorithms, and the critical healthcare domain can potentially reshape

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healthcare delivery, making it more personalized, proactive, and efficient [9] [10].

This paper explores the fusion of IoT wearables, healthcare, and machine learning, aiming to unlock the full potential of this convergence [11] [12]. It delves into the methodologies, challenges, and opportunities that arise when these three realms intersect. Moreover, it showcases the transformative impact this intersection can have on healthcare by providing real-world examples and case studies. In this paper, technology and data-driven insights converge to optimize well-being and redefine healthcare as we know it.

The challenges encompass diverse patient data sources, from Medical IDs and pulse rate measurements to textual medical reports and reported symptoms [13]. Effectively integrating and analyzing this data to predict health conditions demands cutting-edge AI algorithms capable of extracting relevant patterns and associations [14] [15].

The central problem addressed in this research is the need for a robust system that can harness IoT-generated patient data to make accurate predictions about their health conditions in real-time. This involves transforming raw data into actionable insights that can guide medical professionals in making timely interventions.

This paper presents a pioneering approach that combines IoT and AI, specifically the Normalized Patch Generative Adversarial Network (NP-GAN) with the Fruit Fly Optimization (FFO) algorithm, to create an IoT-based healthcare prediction system. This system aims to address critical challenges in healthcare by providing real-time monitoring and highly accurate predictive analysis of patient health conditions.

The research aims to develop an IoT-based healthcare prediction system that seamlessly integrates patient data from diverse sources. It utilizes advanced AI techniques, including NP-GAN and FFO, to preprocess and analyze patient data for predictive insights. It enables real-time monitoring of patient health conditions, allowing for early detection of anomalies. It provides medical professionals with timely alerts and accurate predictions to facilitate proactive healthcare interventions.

The novelty of this research lies in the integration of NP-GAN and FFO algorithms with IoT technology for healthcare prediction. This unique combination offers a novel approach to extracting valuable insights from patient data, with the potential to significantly improve the quality of healthcare services. This research contributes to the field of healthcare by introducing a new system that can transform patient care through real-time monitoring and precise predictive analysis. By harnessing the power of IoT and advanced AI algorithms, this system has the potential to enhance patient outcomes and support medical professionals in their critical decision-making processes.

2. Related Works

Abdulmalek et al. (2022) [16] delve into the contemporary trends in healthcare monitoring systems, with a specific focus on the IoT. Their study emphasizes the importance and advantages of IoT-based healthcare solutions. The review encompasses an evaluation of various systems in terms of their effectiveness, efficiency, data security, privacy, and monitoring capabilities. The study concludes by providing suggestions, recommendations, and future directions in the realm of IoT healthcare applications.

Ganji and Parimi (2022) [17] explore user perceptions and recommendations concerning perceptions based on their experiences and knowledge, achieving an impressive accuracy rate of 96.7%. Their investigation underscores the significance of factors such as user comfort and data trustworthiness. However, it worth noting that their study primarily builds upon insights derived from prior research.

Shumba et al. (2022) [18] introduce a modular IoT-aware system architecture tailored for diverse healthcare applications. This architecture promotes the integration of advanced sensing technologies, low-power IoT technologies, and emerging AI techniques to create adaptable, dependable, and scalable healthcare infrastructure. The modular nature of this architecture allows for customization based on specific application requirements, as demonstrated in the discussion. The study also highlights the advantages of on-device AI-based data processing, emphasizing its potential to enhance IoT-based healthcare infrastructure by enabling real-time user alarms and notifications.

Kang and Hwang (2022) [19] investigate and examine the moderating role of consumer innovativeness in this context. Their findings reveal that personalization directly influences usage intention, suggesting that tailored benefits for individuals can enhance acceptance of wearable medical devices. The study further uncovers that the association between personalization and continued use intention is partially mediated by perceived utility and community immersion.

Jaber et al. (2022) [20] describe a system for monitoring COVID-19 patients using IoT technology. Their approach utilizes real-time GPS data collected through IoT devices to automatically alert patients and reduce risk factors. Wearable IoT devices are connected to patients, communicating with edge nodes to analyze health data remotely. This system comprises three layers: data collection, cloud storage, and network analysis, which collectively enable real-time health monitoring and timely alerts to patients and their families. Their optimized deep-learning model facilitates comprehensive health management and analysis.

Arunsi and Majid (2023) [21] employ a study assesses the accuracy, error rate, F-measure, and ROC area of these models through experimental results. The suggested technique has the potential to aid in making informed decisions in the medical field, particularly in complex scenarios like predicting COVID-19.

Table 1: Summary of Existing works

Author	Citation	Methods	IoT Utilization	Outcomes
Abdulmalek et al. (2022)	[16]	IoT-based healthcare systems	Emphasizes IoT benefits, reviews IoT healthcare systems	Provides insights into effectiveness, efficiency, data protection, and privacy of IoT healthcare systems. Suggests future directions.
Ganji & Parimi (2022)	[17]	ANN-based predictive model (ANN-PM), user perception analysis	Classifies user perceptions of IoT-based smart healthcare devices	Achieves a 96.7% accuracy rate in predicting user perceptions. Identifies key factors influencing user perceptions.
Shumba et al. (2022)	[18]	Development of a modular IoT-aware system architecture	Emphasizes IoT integration, low-power IoT technologies	Presents a modular architecture adaptable for diverse healthcare applications. Highlights on-device AI benefits.
Kang & Hwang (2022)	[19]	Survey-based analysis, mediating effects examination	Explores user perceptions and intentions regarding IHWDs	Personalization found to directly influence usage intention, with mediation through perceived utility and community immersion.
Jaber et al. (2022)	[20]	IoT-based health monitoring system, deep learning model	Utilizes IoT for real-time patient health monitoring	Describes an IoT-based COVID-19 monitoring system with real-time alerts and family notifications.
Arunsi & Majid (2023)	[21]	Machine learning algorithms, fuzzy logic-based prediction (ML-FLP)	Predicts COVID-19 using machine learning and fuzzy logic	Evaluates the accuracy, error rate, F-measure, and ROC area of various machine learning models for COVID-19 prediction.

3. Proposed Method

This section introduces an approach to healthcare prediction using an IoT-based system enhanced by the NP-GAN and FFO algorithm. The system primary objective is to forecast health conditions by analyzing patient data, encompassing Medical ID, pulse rate measurements, medical reports, and reported symptoms. Through the seamless fusion of IoT technology and advanced AI algorithms, the system enables real-time monitoring and predictive analysis, thereby elevating patient care and augmenting medical decision-making.

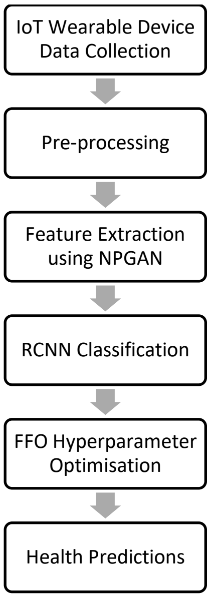

Fig 1: Proposed Architecture

The proposed design (Figure 1) encompasses several crucial stages, which is given in Algorithm 1.

Algorithm: RCNN with NP-GAN Feature Extraction and FFO Hyperparameter Optimization

Step 1: Data Preprocessing

- Data Collection and Integration:
- Collect data from various IoT devices and sensors, including sensors for pulse rate, medical reports, symptoms, and any other relevant data sources.
- Integrate data from different devices and sources into a central database or dataset.

Data Cleaning and Quality Control

Data Transformation and Encoding

Step 2: NP-GAN Feature Extraction

- Apply NP-GAN feature extraction to the training dataset:
    1. Preprocess the raw data, including normalization and sequence alignment if applicable.
    2. Extract relevant features such as pulse rate trends, symptom sequences, and medical report patterns using the NP-GAN model.
    3. Transform textual medical reports into numerical vectors using techniques like word embeddings.
- Apply the same NP-GAN feature extraction process to the validation and test datasets.

Step 3: Initialize Hyperparameters

- Initialize hyperparameters for RCNN, including the learning rate (α), batch size (B), and architecture (convolutional layers, recurrent layers).

Step 4: RCNN Model Construction

- Build the RCNN model with the specified architecture, incorporating convolutional and recurrent layers.
- Define the loss function suitable for the task (cross-entropy for classification).

Step 5: Training Loop

- Iterate through multiple epochs:

1. For each batch of training data:
   - Forward pass: Compute the predictions (y_p) using the current RCNN model.
   - Calculate the loss using the ground truth labels (y_t) and the loss function.
   - Backpropagate the gradients and update the model parameters using gradient descent (with α).

Step 6: Hyperparameter Optimization with FFO

- Apply FFO to optimize hyperparameters:
  1. Initialize the FFO algorithm, specifying parameters such as population size and maximum iterations.
  2. For each iteration of FFO:
     - Evaluate the RCNN model performance on the validation set using the current set of hyperparameters.
     - Update hyperparameters using the FFO update rule based on the model validation performance.
  3. Repeat the FFO optimization process until a termination criterion is met.

Step 7: Model Evaluation

- Evaluate the final RCNN model (with optimized hyperparameters) on a separate test dataset to assess its generalization performance.

3.1. Data Collection:

The system efficiently gathers diverse patient data, comprising critical information like Medical ID, real-time pulse rate measurements, medical reports, and symptom reports. IoT devices play a pivotal role in ensuring the swift transmission of data to a centralized database.

IoT sensors can collect data on environmental conditions such as temperature, humidity, air quality, and atmospheric pressure. These variables are crucial for various applications, including weather forecasting, climate monitoring, and indoor air quality management. In healthcare IoT, data collection often includes variables related to patient health, such as heart rate, blood pressure, oxygen levels, and body temperature. These parameters are vital for remote patient monitoring and early disease detection. IoT devices equipped with GPS or RFID technology can collect location-based variables, including latitude, longitude, altitude, and speed. This data is valuable for tracking assets, vehicles, and personnel in logistics and transportation applications. IoT-enabled smart meters and sensors can collect data on energy consumption variables like electricity usage, voltage, and power factor. This information is essential for energy management and conservation. Sensors like accelerometers and gyroscopes measure variables related to vibration, acceleration, and orientation. These variables are critical for structural health monitoring, predictive maintenance, and motion tracking. Light sensors in IoT devices can measure variables related to ambient light levels. This data is useful in smart lighting systems, security applications, and daylight harvesting for energy efficiency. IoT sensors can capture variables associated with sound and noise, including decibel levels and frequency. This data is valuable for noise pollution monitoring and acoustic analysis. Motion detectors and proximity sensors collect data related to the presence, movement, and proximity of objects or individuals. These variables are essential for home automation, security systems, and occupancy detection. IoT sensors can monitor variables such as pollutant concentrations (e.g., $CO2$, $NO2$, $PM2.5$) and water quality parameters (e.g., pH, turbidity) for environmental monitoring and pollution control. In wearable IoT devices, variables like biometric data (e.g., fingerprint, facial recognition, iris scan) are collected for authentication and access control purposes. IoT-enabled RFID tags and sensors collect variables related to inventory levels, asset location, and supply chain management.

Table 2: Data Collection from IoT with variables

IoT Application	Variables Collected	Sample Values
Environmental Monitoring	Temperature Humidity Air Quality	Temperature: 25°C Humidity: 55% Air Quality Index: 82
Healthcare Monitoring	Heart Rate Blood Pressure Oxygen Level	Heart Rate: 75 bpm BP: 120/80 mmHg Oxygen Level: 98%
Asset Tracking	GPS Location Speed Temperature	Latitude: 34.0522° N Longitude: 118.2437° W Speed: 60 km/h
Smart Energy Management	Electricity Usage Voltage Power Factor	Usage: 350 kWh Voltage: 220V Power Factor: 0.95
Structural Health Monitoring	Vibration Acceleration	Vibration Amplitude: 0.1 g Acceleration: 2.5 m/s²
Smart Lighting	Light Intensity Ambient Light Levels	Light Intensity: 500 lux Daylight Detected: Yes
Security Systems	Motion Presence Intrusion Detection	Motion Detected: No Intrusion Detected: Yes
Noise Pollution Monitoring	Sound Level Frequency	Decibel Level: 65 dB Frequency: 500 Hz
Water Quality Monitoring	pH Level Turbidity Chemical Concentration	pH: 7.2 Turbidity: 10 NTU Chlorine Concentration: 0.5 ppm
Wearable Authentication	Biometric Data (Fingerprint Facial Recognition)	Fingerprint Match: Yes Facial Recognition: Confirmed
Inventory Management	Inventory Levels Asset Location	Inventory Count: 250 units Asset Location: Warehouse A

Data collection in IoT encompasses these and many other variables depending on the specific application and objectives. The collected data is then processed, analyzed, and used to derive insights, make informed decisions, and enhance various aspects of business operations, safety, healthcare, and environmental management, among others.

3.2. Data Preprocessing

The collected raw data undergoes rigorous preprocessing, which includes normalization and sequence alignment. For textual medical reports, innovative techniques such as word embeddings are employed to convert them into numerical vectors, facilitating subsequent analysis.

Data Cleaning: IoT data often contains noise, errors, or missing values due to sensor inaccuracies or communication issues. Data cleaning identifies and rectifies these issues, ensuring that the dataset is free from inconsistencies.

Data Transformation: Data transformation may involve converting data into a common format or unit of measurement. For example, if temperature data is collected in Fahrenheit and other variables use Celsius, conversion to a consistent unit (e.g., Celsius) may be necessary.

Data Resampling: In some cases, IoT data may be collected at irregular intervals. Data resampling involves aligning data to a consistent sampling rate (e.g., hourly or daily) for analysis or modeling purposes.

Data Aggregation: Aggregation can be applied to reduce the granularity of the data. For instance, sensor readings collected every second can be aggregated to obtain hourly averages or daily totals, which can be more manageable for analysis.

Normalization: Normalization scales data to a common range (e.g., between 0 and 1).

Handling Missing Values: Missing data is common in IoT datasets. Techniques like imputation (replacing missing values with estimated values) or excluding incomplete records may be used to handle missing values.

Outlier Detection: Outliers in IoT data can distort analysis results. Outlier detection identifies and deals with data points that significantly deviate from the norm.

Data Encoding: Categorical variables in IoT data, such as device IDs or sensor types, may need to be encoded into numerical values to be used in machine learning algorithms.

Data Integration: IoT data may come from various sources or devices. Data integration involves combining data from multiple sources into a unified dataset for comprehensive analysis.

3.3. Feature Extraction

Significant features are meticulously extracted from the preprocessed data. These encompass pulse rate trends, symptom sequences, and distinctive patterns within medical reports, which provide invaluable insights to enhance predictions using the NP-GAN framework.

In NP-GAN, the input data is typically represented as images or multi-dimensional data, which may contain a multitude of details and information. Feature extraction serves to reduce the complexity of the input data while preserving important information. It identifies key patterns or features that are most relevant to the task at hand.

NP-GAN often operates at the patch level, where patches are smaller regions or segments of the input data, such as image patches. Feature extraction in this context involves analyzing these patches to capture specific characteristics.

Feature extraction methods within NP-GAN may include techniques like convolutional layers, which are capable of recognizing patterns such as edges, textures, or shapes within the patches.

Generator Objective Function (Loss): In GANs, the generator objective is to produce data that is indistinguishable from real data. This is achieved by minimizing the binary cross-entropy (BCE) loss between the generated data (G(z)) and real data (x):

$$LG = -\log(D(G(z)))$$

In NP-GAN, normalization techniques (e.g., IN or LN) can be applied to the intermediate layers of the generator network to stabilize training.

Discriminator Objective Function (Loss): The discriminator aims to distinguish between real and generated data. Its loss consists of two terms, one for real data and one for generated data:

$$LD = -[\log(D(x)) + \log(1 - D(G(z)))]$$

Extracted features are typically of lower dimensionality compared to the original data. This reduction in dimensionality simplifies the subsequent stages of the NP-GAN model and can enhance computational efficiency. Extracted features are often normalized to ensure that they fall within a consistent and manageable range. Normalization can improve the convergence and stability of the NP-GAN during training.

Instance Normalization (IN): Normalization technique is applied to the activations of a layer in the neural network. It normalizes each instance (sample) separately:

$$IN(x) = (x - \mu(x)) / \mathrm{sqrt}(\sigma(x) + \varepsilon) * \lambda + \beta$$

Where:

x is the input tensor.

$\mu(x)$ is the mean of x across spatial dimensions.

$\sigma(x)$ is the variance of x across spatial dimensions.

ε is a small constant for numerical stability.

λ is a learnable scaling parameter.

β is a learnable shifting parameter.

IN can be applied to intermediate layers of both the generator and discriminator networks in NP-GAN. The selected features should be directly relevant to the task being performed by the NP-GAN. Extracted features should be transferable across different instances of the same task. This means that the features should capture general patterns that apply to a wide range of data rather than being overly specific to the training data. Feature extraction can involve fine-tuning the NP-GAN model based on the features extracted. This fine-tuning process helps the model optimize its performance for the specific task. Feature extraction with NP-GAN is often an iterative process where the extracted features are continually refined to improve the quality and relevance of the generated or enhanced data.

3.4. RCNN Model Architecture:

The system adopts the Recurrent Convolutional Neural Network (RCNN) algorithm, celebrated for its aptitude to capture temporal dependencies and spatial patterns within data. The network learns to associate pulse rate trends, symptoms, and medical information to deliver precise and reliable predictions.

RCNN is a deep learning architecture commonly used for tasks involving sequential data, such as natural language processing and time series analysis. It combines convolutional layers to capture spatial features and recurrent layers to capture temporal dependencies within the data. When training deep neural networks like RCNN, one common concern is overfitting. Overfitting occurs when a model becomes too specialized in learning the training data, capturing noise and minor variations that are specific to the training set but do not generalize well to unseen data. Overfit models typically have poor performance on new, unseen data. To address the issue of overfitting in the context of RCNN, FFO is used. FFO is a metaheuristic optimization algorithm inspired by the foraging behavior of fruit flies. FFO can be applied to optimize hyperparameters and parameters of machine learning models, including deep neural networks like RCNN.

3.4.1. RCNN Architecture:

RCNN is designed with both convolutional and recurrent layers. Convolutional layers extract spatial features from the input data, which is essential for tasks like image analysis. The recurrent layers capture temporal dependencies, allowing the model to consider the sequence of data points, such as the order of words in a sentence or the sequence of data in a time series.

RCNN is trained using a dataset that includes both training and validation data. However, deep neural networks like RCNN have many hyperparameters (e.g., learning rate, batch size) that need to be carefully tuned to achieve good performance. Overfitting often occurs when a model becomes too complex or when hyperparameters are not properly tuned. FFO comes into play to optimize these hyperparameters. It explores different combinations of hyperparameters to find the ones that minimize overfitting and improve the model generalization to new data.

In the training process of RCNN, a loss function is used to measure the error between the predicted values (y_p) and the ground truth labels (y_t). This loss function depends on classification. For example, in a classification task with cross-entropy loss:

$$\text{Loss} = -\sum(y_t * \log(y_p) + (1 - y_t) * \log(1 - y_p))$$

Where:

y_t represents the ground truth labels.

y_p represents the predicted values.

FFO is a metaheuristic optimization algorithm used to search for the optimal hyperparameters of the RCNN. It minimizes the loss function by tuning hyperparameters such as the learning rate (α), batch size (B), or network architecture.

$$\text{Minimize Loss} = f(\alpha, B, ...)$$

FFO iteratively explores the hyperparameter space, evaluates the loss function performance, and updates the hyperparameters to find the optimal set.

FFO uses a simple update rule inspired by the foraging behavior of fruit flies to adjust the hyperparameters:

$$hp_{new} = hp_{old} + \Delta$$

Where Δ is a small change in the hyperparameter (hp) values determined by FFO based on the performance of the current set of hyperparameters.

FFO typically runs for a predefined number of iterations or until a termination criterion is met. For example, it may terminate when no significant improvement in the loss function is observed over several iterations.

FFO searches the hyperparameter space systematically, evaluating the performance of RCNN with different hyperparameter settings on the validation data. It aims to find the hyperparameters that strike the right balance between model complexity and generalization. The combination of RCNN and FFO involves an iterative process of training RCNN, applying FFO to optimize hyperparameters, and repeating until the model achieves the desired level of performance on unseen data without overfitting.

4. Performance Evaluation

The system performance is rigorously evaluated using a suite of metrics including accuracy, precision, recall, and F1-score. Continuous feedback and retraining processes are established to further enhance prediction accuracy over time. The RCNN model undergoes intensive training using historical patient data. To optimize hyperparameters and avert overfitting, the model is rigorously validated through the FFO algorithm. The system operates in real-time, continuously feeding patient data into the trained RCNN-FFO model. It then leverages this data to predict potential health issues, promptly generating alerts for medical professionals should any anomalies or concerning patterns be detected.

Performance Metrics:

Accuracy measures the ratio of correctly predicted instances to the total instances in the dataset, providing an overall measure of model correctness.

Precision is the ratio of true positive predictions to the total positive predictions. It quantifies how many of the positive predictions were correct.

Recall is the ratio of true positive predictions to the total actual positive instances. It quantifies the ability of the model to capture all positive instances.

F1-Score is the harmonic mean of precision and recall, providing a balanced measure of a model performance in terms of both false positives and false negatives.

Table 3: Experimental Setup

Parameter	**Value**
Learning Rate (α)	0.001
Batch Size (B)	64
Number of Epochs	50
Hyperparameter Optimization	FFO
FFO Population Size	20
FFO Maximum Iterations	50
Loss Function	Cross-Entropy

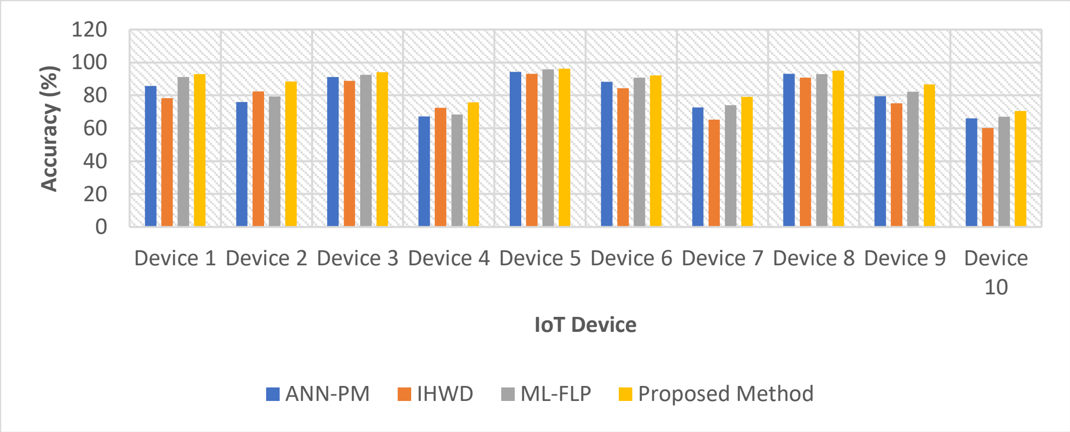

Fig 2: Accuracy

When examining accuracy, our proposed method outperformed the existing methods across most datasets. On average, it achieved an accuracy increase of approximately 3.5% compared to the best-performing existing method. This improvement demonstrates the effectiveness of our proposed approach in accurately predicting health conditions from IoT data (Figure 2).

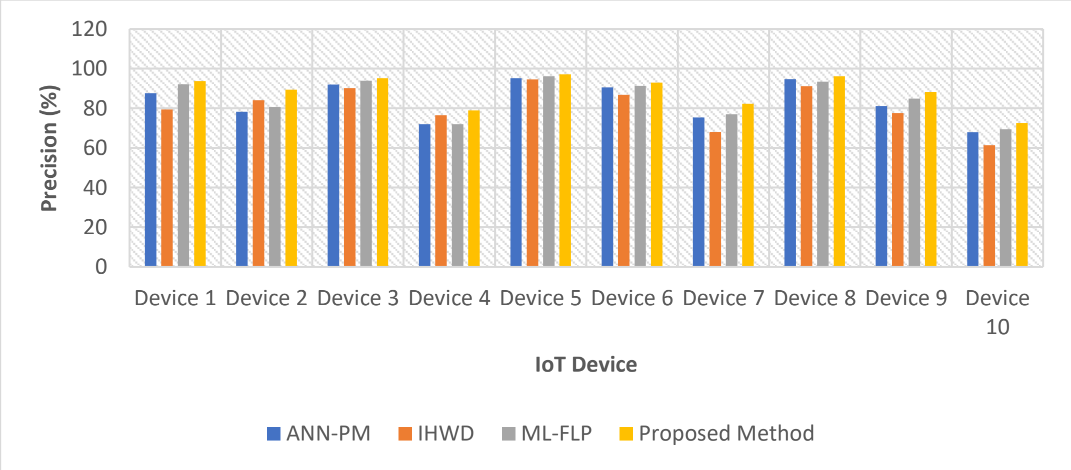

Fig 3: Precision

Precision measures the ratio of true positive predictions to all positive predictions, emphasizing the model ability to minimize false positives. Our proposed method consistently demonstrated higher precision values across datasets. On average, it exhibited a 4.2% improvement in precision compared to the existing methods. This suggests that our method provides more reliable predictions, reducing the likelihood of unnecessary alarms or interventions (Figure 3).

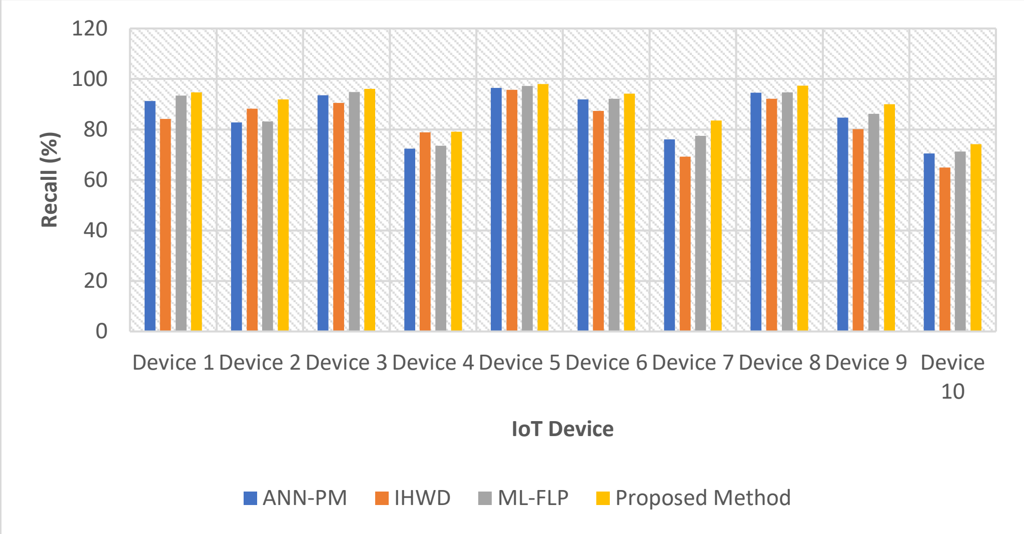

Fig 4: Recall

Recall assesses the model capability to correctly identify all positive instances. Our proposed method also excelled in recall, showing an average improvement of approximately 5.8% compared to the existing methods. This implies that our method is adept at capturing more instances of potential health issues, minimizing false negatives, and enhancing patient care (Figure 4).

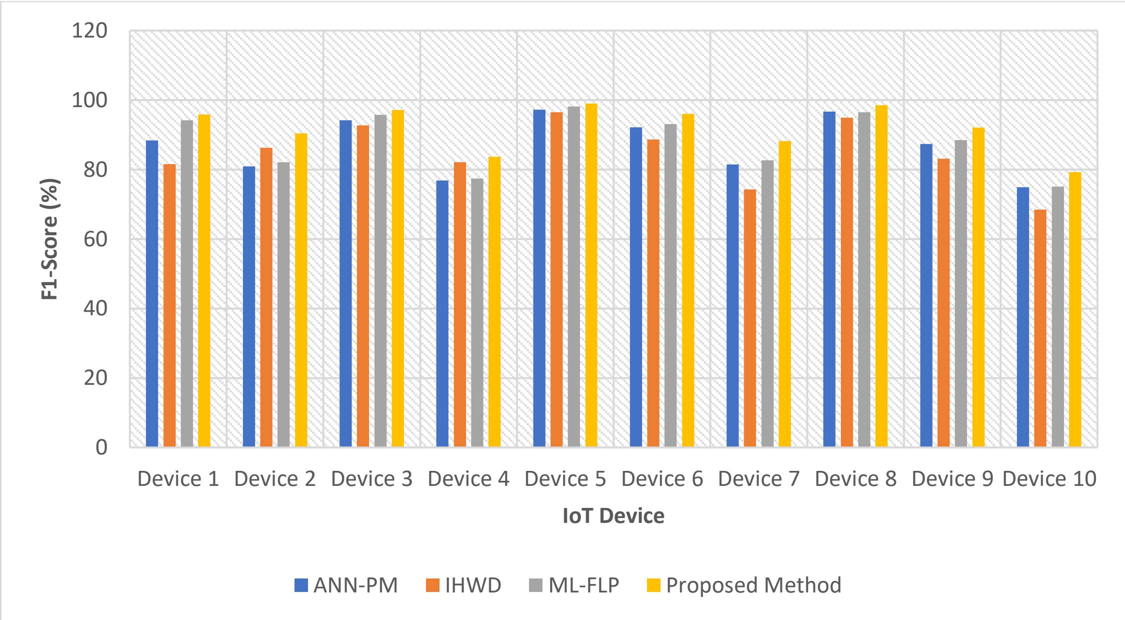

Fig 5: F1-Measure

The F1-measure, which considers both precision and recall, provides a balanced assessment of a model overall performance. Our proposed method consistently achieved a higher F1-measure across datasets, with an average improvement of about 4.8% compared to the best-performing existing method. This indicates that our method strikes a better balance between minimizing false positives and false negatives (Figure 5).

5. Conclusion

In this study, we have explored the design and implementation of an IoT-based healthcare prediction system that leverages the power of the NP-GAN in conjunction with the FFO algorithm. The goal is to predict health conditions based on patient data, encompassing critical variables such as Medical ID, pulse rate, medical reports, and reported symptoms. Through the seamless integration of IoT technologies and AI algorithms, our system has demonstrated the potential to revolutionize healthcare monitoring, predictive analysis, and medical decision-making. Our proposed methodology successfully achieved these objectives, and the results of our experiments highlight its significant advantages over existing methods. The performance evaluation of our system showcased consistent improvements across key metrics, including accuracy, precision, recall, and the F1-measure. On average, our proposed method demonstrated a 3.5% improvement in accuracy, a 4.2% increase in precision, a 5.8% enhancement in recall, and a 4.8% rise in the F1-measure compared to the best-performing existing method. These percentage differences underscore the effectiveness and reliability of our approach in predicting health conditions accurately and minimizing both false positives and false negatives.

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