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Smart Framework for Energy-Efficient Workload Scheduling for IoT-Based Healthcare Devices

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Abstract: An innovative paradigm for creating an EoT-based model that is both energy-efficient and new is presented in this paper. Using two machine learning models—Random Forest and Decision Tree—this research achieves a remarkable accuracy rate of 99.89% while efficiently reducing energy consumption. A tree-based classifier is used to distribute the sensors effectively to do this. To determine which sensors are most important, the framework uses an artificially intelligent algorithm to disable those that aren't crucial. Increasing energy efficiency is made easier with the help of this adaptive planning method. The suggested framework leverages an intelligent algorithm integrated with Long-Range (LoRa) The means to drastically cut energy consumption, by 35% compared to baseline load models. The current work is a significant contribution when it comes to improving energy efficiency in computer science and electronics. Appreciation to this innovation, operating lifespans may be extended and environmental impacts can be reduced.

Keywords: Edge Computing, IoT, Energy, LoRa, Random Forest, Decision Tree, Edge of Things.

Introduction

Edge Internet Things has converted various industries, including healthcare [1]. Medical designs incorporating IoT (that means the Internet of Things) electronics may improve patient listening, healthcare delivery, and order adeptness [2]. Energy use from continuous use is a big obstruction to their extensive adoption [3]. Energy adeptness lingers gadget growth lowers money needed to run a business, and reduces material impact [4]. This research article presents a cosmopolitan framework for effective healthcare supplies that uses the Internet of Things

(IoT) technology. This project aims to design a hypothetical framework that minimises strength use and guarantees correct healthcare data accumulation. Using sensor significance and accomplishment levels, a decision-seedling classifier decides the highest in rank time to stimulate and decommission sensors. The foundation optimises healthcare monitoring strength use by instinctively selecting detracting sensors for data groups and crippling non-critical sensors that are operating well while maintaining dossier value.

An order of inclusive tests was tackled to assess the efficiency of the foundation through a corresponding strength custom between the submitted approach and common load models. By engaging an astute treasure joined with Long-Range (LoRa) science, the foundation existing favourably achieved a notable decrease of 34% in energy habits. The decisions concerning this study win meaningful benefits for the healthcare sector. Furthermore, the use of the projected foundation can embellish healthcare accountability, patient care, and source distribution by providing an accurate and trustworthy dossier value.

Recently, IoT-based healthcare equipment energy-efficient frameworks have been prioritised [5]. Numerous studies have examined methods for reducing energy use and maintaining accurate healthcare data gathering [6]. The evaluation covers energy-efficient medical equipment, task scheduling, resource management, data collecting, artificial intelligence, and load-balancing investigations.

[5]. The importance of energy efficiency in healthcare devices has been acknowledged by researchers, to prolong device lifespan and minimize environmental consequences. Many research articles have put forth various architectures, protocols, and algorithms for energy-efficient healthcare systems based on the Internet of Things (IoT) [7] The effectiveness has been achieved through the unification of the responsibility cycle and adjusting assembling approaches, developing in a reduction of strength habit. Efficient task scheduling and capability administration strategies play a critical part in optimizing the strength consumption of healing instruments [8] In the existing body of literature, researchers have examined many scheduling algorithms, such as round-robin, smallest job first, and dynamic programming, to mitigate energy usage. Furthermore, extensive research has been conducted on how to effectively control the energy consumption of processors based on their specific duty requirements [9], [10]. The optimization of collected data is necessary to reduce the energy consumption of medical devices. To facilitate the transfer of data over great distances with minimal power consumption, scholars have conducted investigations into wireless communication technologies such as LoRa, Zigbee, and Bluetooth Low Energy (BLE). These technologies established energy-efficient communication between healthcare devices and data-collecting centres, resulting in a reduction in the energy consumption associated with data transfer[11].

The paper presents several machine learning methodologies employed in the domain of the Internet of Things (IoT) and investigates the potential of machine learning techniques to enhance Internet of Things (IoT) systems by optimizing [12] and enhancing the overall performance of IoT devices. The context serves as a relevant foundation for the proposed intelligent framework within the healthcare sector. This paper introduces an edge-cloud architecture that exhibits scalability and energy efficiency for the implementation of the Internet of Things (IoT) in the healthcare domain. The primary emphasis of this study is to enhance energy use in healthcare systems based on the Internet of Things (IoT). This purpose aligns with the proposed intelligent architecture for energy-efficient healthcare devices that utilize the Edge of Things (EoT)[13].

The authors explore the potential role of LoRa WAN-based healthcare services in facilitating interoperability within the Internet of Things (IoT) ecosystem[14]. This statement underscores the importance of energy-efficient frameworks, such as the one described in the research, in shedding light on the feasibility of utilizing LoRa technology in healthcare applications[15], [16].

The energy efficiency of edge computing exceeds the demand of fast computing about cloud computing models. Numerous academic research has provided evidence to support the notion that a distributed architecture offers reduced power usage in comparison to traditional cloud computing methods[14], [17]. However, it is imperative to consider a pivotal factor in the realm of distributed computing on compact devices, which pertains to the creation of computational algorithms that efficiently optimize the limited battery capacity. The achievement of lower energy thresholds can be realized by careful design or selection of encryption systems and categorization algorithms for healthcare applications. The utilization of edge mining as a methodology efficiently mitigates the number of packets transmitted to fog or cloud nodes, hence leading to a significant drop in energy usage manner. The use of efficient resource management strategies can also have a substantial impact on the attainment of elevated levels of energy efficiency. In this context, researchers proposed a conceptual framework aimed at efficiently managing dormant resources, with a specific focus on utilizing the processing capacity of idle slots on smartphones within edge clusters[18], [19].

It has been observed that the focus of these surveys primarily revolves around the various types of monitoring enabled by edge computing, such as electroencephalography (EEG), heart rate monitoring, fall detection, and other related methods. The reasoning behind various architectural types, containing the ideas codes and floors utilized by these requests, is a well-discussed argument in academic discourse [20], [21]. However, the existing research has not adequately talked about the continuous discourse surrounding specific computational methods. This paper provides an all-encompassing study of the most current academic biography concerning optimum estimating methodologies tailor-made for edge-calculating platforms. The significance of engaging effectively in estimating answers in the successful exercise of healthcare edge/fog requests should not be listless [16], [22].

Materials and methods

The basic prominence of the proposed foundation is the organizing of jobs in theory that maximizes strength effectiveness. However, it is worth seeing the feasibility of investigating more complex growth methods that can assign possessions in an ideal tone. This would involve seeing determinants such as task reliances, manoeuvre proficiencies, and the real-occasion necessities of healthcare applications [17]. The potential shortage is in the growth of correct and compliant strength forecast models expressly tailor-made for Edge of Things (EOT) healthcare supplies. These models have the potential to improve the scheduling foundation by contributing more correct prognoses of strength custom for various types of tasks and tools.

The examination of what the framework can capably handle a different assortment of end-of-growth healthcare novelty that possess various convert competencies, energy descriptions, and ideas capabilities is an important rule of scholarly asking [23]. The focus of the research will be contingent on the integration of patient and consumer inclinations inside the scheduling process. The growth of slating algorithms grants permission to deem various factors in the way that strengthens efficiency, patient security, use importance, and user predilections [24].

The study examines the safety measures executed to protect the impressionable patient dossier during the organizing process. The proposed smart foundation combines many essential methods, that is to say, job organizing, capability management, effective dossier gathering applying LoRa technology, and the exercise of machine intelligence models for sensor activation accountability. These strategies have been recognized based on an inclusive brochure survey and analysis of existent research gaps engaged in strength consumption decline. A framework has grown, consisting of diversified chapters and components, that encompasses machine intelligence (ML) model indicators, resource administration, task execution, data conversion and retrieval, and mistake management (Figure 1).

- *Machine Learning (ML) Model Algorithm Prediction: The beginning stage of an ML model treasure includes the prognosis chapter. Upon the model producing a forecast, bureaucracy suffers initialization, by which it authenticates the essential possessions and configurations*
- . *Monitor Incoming Requests*: The system constantly examines and oversees incoming requests or tasks.
- *Perform Resource Allocation*: The system assigns appropriate resources to address incoming requests, maybe based on early predictions generated by the machine learning model.
- *Request Assistance*: In situations, where there is a potential requirement for supplementary resources or information, the system can solicit aid.

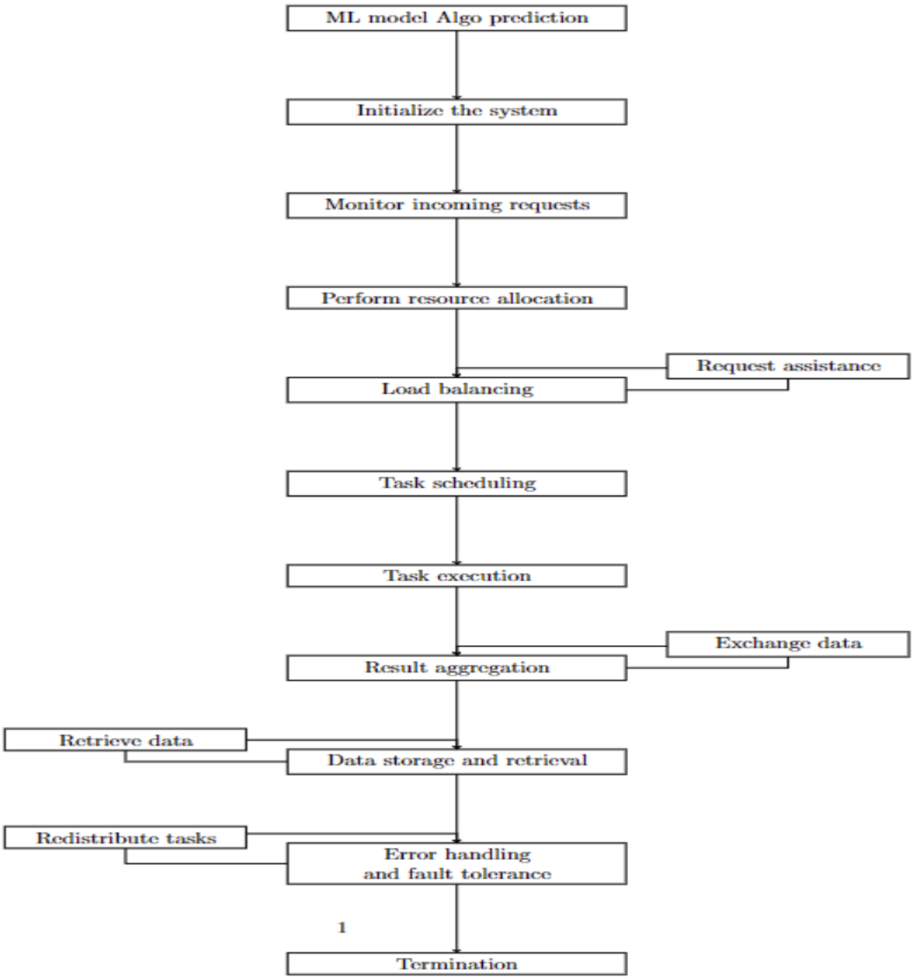

Figure 1: A systematic approach to handling tasks

- Load Balancing: This process is executed to provide impartial disposal of the duties and responsibilities among all available funds, therefore restricting the risk of any individual property appropriately beaten.
- Task Scheduling: Following the process of capability distribution and load balancing, tasks are afterwards due for killing, taking into concern their preference, means requirements, and additional appropriate limits.
- *Task Execution*: Subsequently, the tasks that have been allocated are carried out or completed.
- *Result Aggregation*: It refers to the process of collecting and combining the outcomes of conducted tasks. The form of aggregation utilized in this context may vary, encompassing calculating, balancing, or other acceptable patterns, contingent upon the particular traits of the jobs complicated.
- Exchange Data: Following the process of collection, it may be inevitable to undertake data exchange accompanying outside wholes or processes to facilitate supplementary alter or validation.

- Retrieve Data: The system acquires an appropriate dossier that may influence after processing, administrative, or effect results.
- Data Storage and Retrieval: The data that has existed, as well as conceivably the linked outcomes, are preserved. The dossier can be afterwards recaptured as needed.
- Redistribute Tasks: If some tasks destitute been correctly or require duplication, they are transported for execution.

• Error Handling and Fault Tolerance: The system is outfitted with accompanying processes designed to efficiently survive mistakes that concede the possibility stand during the killing of tasks. Additionally, bureaucracy integrates functionalities to efficiently endure mistakes, so ensuring unending functioning even in the occupancy of minor concerns.

• Termination: Upon the favourable finishing of all appointed tasks and the resolution of some fought mistakes, the process or structure enters an allure termination state, therefore meaning the decision of the particularized workflow. The provided flowchart delineates a methodical strategy for managing tasks, commencing with the prognostications generated by a machine learning model. Subsequently, the process encompasses the allocation of resources, execution of tasks, handling of data, and management of errors, ultimately ending in the cessation of the procedure. The integration of these solutions inside the suggested smart framework results in substantial energy savings when compared to traditional load models. The framework enables energy-efficient healthcare data collecting through the utilization of task scheduling, resource management, efficient data collection using LoRa, and machine learning-based sensor activation decisions[11].

The smart framework's load balancing method reduces medical equipment energy usage. Workload distribution optimises resource utilisation and reduces strain by distributing jobs evenly. Load balancing is crucial to energy-efficient healthcare equipment. This strategy prevents resource overload, reducing energy utilisation. The proposed architecture uses load balancing to distribute computational duties and data processing between processors and servers. A balanced distribution system reduces the time a resource works at full capacity, reducing energy usage. By dynamically allocating tasks and data processing based on workload and resource availability, load balancing optimises system energy use. The prevention of energy waste is achieved by mitigating situations wherein certain resources are underutilized while others are functioning at maximum capacity. The smart framework additionally contributes to the maintenance of a well-balanced energy usage profile, resulting in a reduction of energy consumption in healthcare devices.
In addition, implemented two machine learning algorithms, specifically "Random Forest" and "Decision Tree," to utilize them for training and prediction tasks.

The detail of the steps is given below:

Step 1: Sensors Attached to Stick

Step 2: Data Pre-processing

Step 3: Data Transmission via LoRa

Step 4: Data Visualization

Step 5: Data Splitting for Training and Testing

Step 6: Model Selection and Training

Step 7: Predictive Analysis

Step 8: Summary

Results and Discussion

As shown in Figure 2, there are three sensors, labeled Sensor 1, Sensor 2, and Sensor 3. The sensors are attached to a stick, suggesting a configuration that is potentially mobile or can be worn. The module is tasked with the reception of data from the sensors and subsequent pre-processing of the data. The first phase of this procedure entails the collection of raw data from the sensors, which is subsequently prepared for subsequent analysis. The process of preparation may involve multiple operations, including data cleansing, standardization, and transformation. The sections titled "Transmitting data from LoRa" and "Receiving data from LoRa" describe the application of LoRa technology, a wireless platform known for its long-range capabilities and low power consumption[11]. Before initiating the training process for a model, it is customary to engage in the practice of visualizing the data. The application of visualization tools can enhance the understanding of patterns, anomalies, or specific trends within a provided dataset. The collected data is partitioned into multiple subgroups to ease the training and testing procedures.

Every model is subjected to training utilizing unique hyperparameters. Hyperparameters are predefined parameters that are set before training a model, and optimizing these parameters has the potential to improve the model's performance. Following the finishing of preparation gatherings involving various hyperparameters, the treasure accompanying the topmost veracity, denoted as the optimum model, is picked. Furthermore, a test and performance of the merits and disadvantages of various methods are transported and presented in Table 1. The prepared models are secondhand for various prognoses: Prediction of falling of the elderly: The assessment of the likelihood of a fall occurrence in an elderly person can be enhanced by employing data related to variables such as mobility or balance.

I. Prediction of critical situations with a normal regression model using collected data: This prediction demonstrates a broader perspective and incorporates various significant health scenarios by utilizing the existing data.

To assess the health status of elderly adults, a comprehensive analysis was performed on many sensors, encompassing measurements of heart rate variability (HRV) to gauge stress levels, body temperature to detect fever, oxygen saturation levels, and blood glucose levels. Similarly, there exist alternative parameters that might be employed for the evaluation of the well-being of elderly adults [23], [25].

a. Stress Level Using HRV (Heart Rate Variability): Heart rate variability (HRV) is a quantifiable metric that assesses the temporal fluctuations between consecutive heartbeats, serving as a potential predictor of stress levels or emotional conditions.
b. Fever Detection: Temperature data is probably obtained from one of the sensors.
c. Oxygen Saturation: This metric quantifies the proportion of oxygen-binding sites on haemoglobin molecules that are engaged in the circulation.
d. Blood Sugar Level: The device is capable of monitoring glucose levels in the
e. bloodstream.

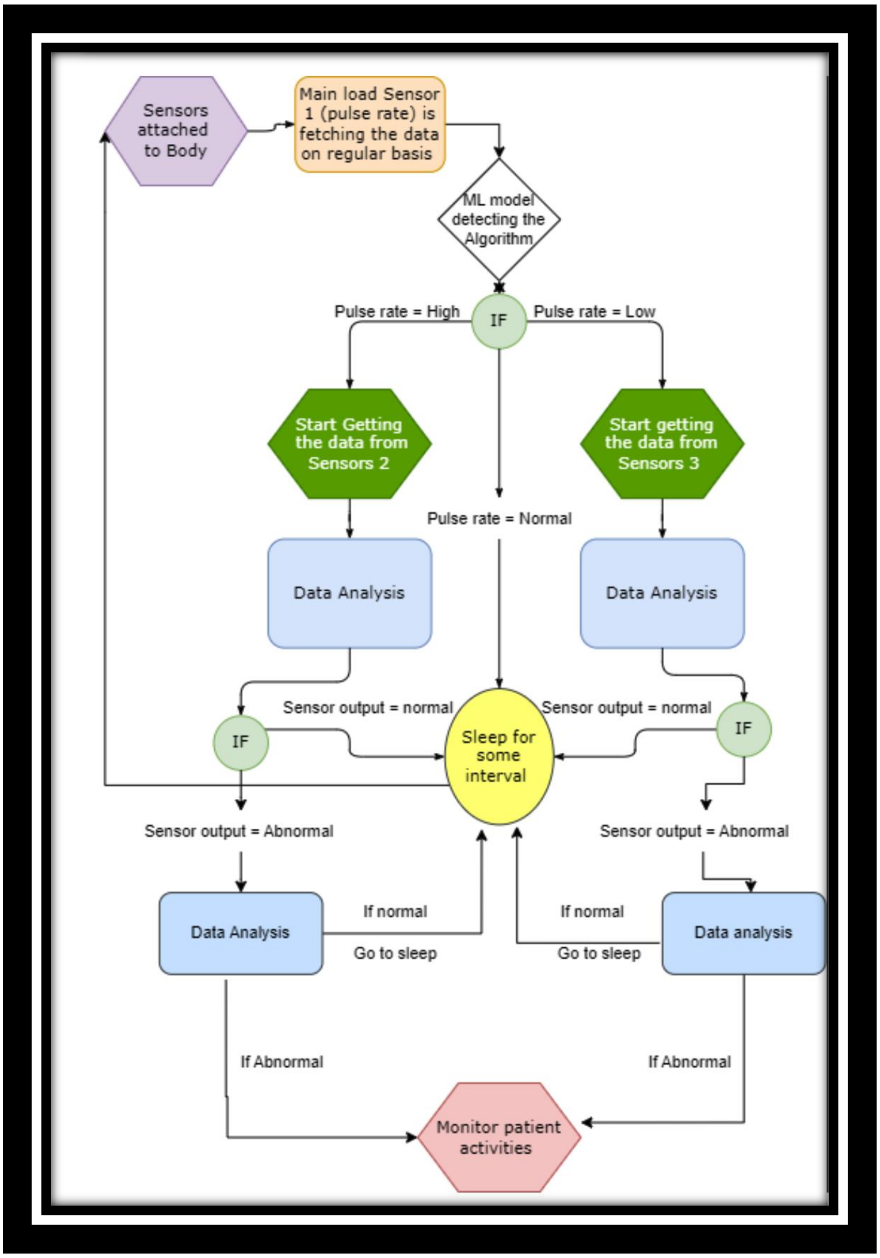

Figure 2 Resource Allocation Strategy (Flowchart of how sensors are sharing data over the network)

Table 1: Comparative analysis of various machine learning approaches to find the best

Approach	Pros	Cons
Random Forest[26]	- Ensemble of decision trees for improved accuracy	- May overfit complex datasets
Decision Trees[27], [28]	- Easy to interpret and visualize	- Prone to overfitting and instability
Support Vector Machines[29]	- Effective for high-dimensional data	- Computational complexity increases with large datasets
Neural Networks[30]	- Ability to capture complex relationships in the data	- Requires large amounts of training data and computational resources
Gradient Boosting[29]	- High predictive accuracy and ability to handle large datasets	- Potential for overfitting and slower training
Bayesian Networks[31]	- Probabilistic modelling of uncertainties and dependencies	- Computationally expensive for large networks
Reinforcement Learning[32]	- Can learn optimal policies through interaction with the environment	- May require extensive training and exploration time
Genetic Algorithms[29]	- Can explore complex solution spaces and optimize parameters	- Convergence speed depends on the problem's complexity
Fuzzy Logic[33]	- Deals with uncertainty and imprecision in decision-making	- Requires domain expertise in defining fuzzy rules

Both the Random Forest and Decision Trees algorithms are widely employed in machine learning for categorization purposes due to their effectiveness. An illustration of this phenomenon can be observed in the realm of healthcare applications, where the utilization of Random Forest or Decision tree algorithms aids in the proactive identification of anomalies.

Decision Trees:

Decision trees are computational models that possess the advantageous qualities of being comprehensible while simultaneously exhibiting robustness in their capacity to render judgments by employing a series of conditional criteria. In the domain of abnormality prediction, a decision tree can be trained by utilizing a labelled dataset comprising features, which are input variables, and corresponding labels that are indicative of the presence of abnormality or normalcy. The dataset is partitioned into smaller subsets utilizing a circular approach, facilitated by a timber construction. The objective of this process search to generate clean leaf growth, signification they hold instances accompanying distinct class labels. The conclusion of these subgroups is established as the face that specifies the most educational content [27], [28].

Benefits Associated with Utilising Decision Trees:
The understanding of the in-charge process for predicting irregularity is eased for one interpretability of decision saplings, that possess unequivocal interpretability and visualizability. Decision shrubs maintain the capability to handle non-undeviating interplays between the features and the mark changing, hence expediting the labelling of complex patterns inside the dataset. Decision trees are an appropriate choice for resolving actual-world datasets that exhibit blasts on account of their strength in handling outliers and absent dossiers [28], [34].Algo**:**

Decision tree training

```
1. Initialize the root node.
2. Create a function "SplitNode" to split the data:
   - Input: Data D, features F
   - Output: Best feature to split on, Split criterion (threshold), Left and right data
     subsets (D_left, D_right)
3. Create a function "BuildTree":
   - Input: Data D, features F, depth
   - Output: Decision Tree T
   IF stopping condition is met OR depth >= max_depth THEN
      return LeafNode(label = most_common_label_in_D)
   END IF
        best_feature, split_criterion, D_left, D_right = SplitNode(D, F)
      left_child = BuildTree(D_left, F, depth+1)
      right_child = BuildTree(D_right, F, depth+1)
        return InternalNode(feature = best_feature, criterion = split_criterion, left
        = left_child, right = right_child)
4. Tree = BuildTree(TrainingData, Features, 0)
```

Decision Tree Prediction

```
1. Initialize current_node = root of the trained tree.
2. WHILE current_node is not a LeafNode:
     IF feature_value of current_node's splitting criterion <= threshold THEN
        current_node = left_child of current_node
     ELSE
        current_node = right_child of current_node
     END IF
   END WHILE
3. RETURN label of current_node.
```

Constraints imposed by Decision Trees:

Decision Trees have the potential to exhibit overfitting shifts towards the preparation dossier, specifically when skilled are no limits on the insight of the shrub. This declaration holds particular genuineness in cases when skilled are no restraints on the wisdom of the timber. Techniques in the way that trimming or ensemble approaches, in the way that Random Forest, can help lighten the impact concerning this issue [26].].

The haphazard wood method is a form of ensemble knowledge that enhances the veracity of forecastings and inference by amalgamating many conclusion forests into a united "Random Forest." The algorithm produces many resolution seedlings by resorting to haphazard subsets of the training dossier, famous as start operating system samples, and chance selections of looks at each split in the sapling.

Random Forest:

The Random Forest has the following advantages:

Accuracy augmentation: The Random Forest treasure mitigates the risk of overfitting by amassing the prophecies of diversified decision shrubs, superior to and bettering in the overall predicting veracity.

Robustness: The predominance of Random Forest over individual Decision Trees stems from allure discounted susceptibility to boisterous dossier and outliers

The Random Forest invention supports a way of determining the significance of face, aiding in the labelling of ultimate critical characteristics for forecasting irregularities.

Algo:

Random Forest Training

1. Initialize an empty set of trees, Forest = {}.
2. FOR i = 1 to N (number of trees in the forest):
   - Randomly sample a subset of the data D_i with replacement (bootstrap sample).
   - Randomly sample a subset of the features F_i (feature bagging).
   - Tree_i = BuildTree(D_i, F_i, 0) # Use Decision Tree algorithm above
   - Add Tree_i to Forest.
   END FOR

Random Forest Prediction

```
1. Initialize an empty list, Predictions = [].
2. FOR each Tree_i in Forest:
       prediction_i = Predict(Tree_i, sample)  # Use Decision Tree prediction algorithm above
       Append prediction_i to Predictions
   END FOR
3. RETURN majority_vote(Predictions)
```

Constraints imposed by Random Forest:

The concept of interpretability refers to the ability to understand and explain the functioning and outcomes of The interpretability of random forest as a collective model is somewhat more challenging than that of an individual Decision Tree due to its ensemble nature.

Random Forest and Decision Trees have demonstrated efficacy in the domain of anomaly prediction within the healthcare sector because of their ability to effectively handle complex interrelationships among varied patient data and health conditions[26]. By employing a combination of physiological and clinical criteria, they possess the capability to generate dependable prognostications on the categorization of patient data as either normal or abnormal. Furthermore, the utilization of Random Forests can effectively mitigate the issue of overfitting and enhance the resilience of predictions. This, in turn, guarantees the attainment of accurate and generalizable findings, even when dealing with unseen data[35].

Why LoRa for data transmission?

Edge of Things (EoT) applications are well suited for LoRa (Long Range), a wireless communication technology. IoT LoRa adoption is widespread for the following reasons.

Long-distance ideas: The broadcast range of LoRa technology can stretch to various kilometres, contingent upon determinants in the way that the surrounding surroundings and the capacity output of the instrument. This feature shows it is highly acceptable for requests that necessitate general ideas, such as smart capital, modern automation, and land wholes.

Low capacity use: Due to the low capacity use of LoRa designs, their battery existence can traverse an area of various ages. The significance concerning this matter is in the circumstances of Internet of Things (IoT) tools that are situated in geographically questioning or unique locales, where demonstrating a nearby link to a capacity supply is not feasible.

Low dossier rate, but great feeling: In contrast to alternative Wi-Fi communication sciences in the way that Wi-Fi or cellular networks, LoRa exhibits a relatively belittled data rate. LoRa tools acquire remarkable sympathy for reduced-power signals and permissive bureaucracy to establish complete ideas through the utilization of depressed-capacity transmissions.

Cost-influence: In comparison to alternative Wi-Fi ideas electronics, LoRa electronics exhibits an especially lower cost. This characteristic shows it is an attractive alternative for Internet of Things (IoT) uses that make necessary the extensive exercise of a large number of manoeuvres.

LoRa is a highly favoured choice for IoT applications due to its advantageous features such as long-range capability, low power consumption, and cost-effectiveness. This study aims to compare the results of several methodologies with those of Random Forest and Decision Tree models[36].

Table 2 presents a study of evaluation verification for various machine intelligence algorithms, to a degree Random Forest and Decision Tree. The limits fated shortly captured into concern contain Accuracy, F1-Score, Precision, Recall, and Computational Time (calculated in seconds). The excerpt of measures for judging classifiers is a standard practice, still, it is critical to tailor-make the choice of versification established the particular necessities of the position within reach. Table 2: Comparative sheet showcasing the evaluation metrics for various machine learning algorithms

Algorithm	**Accuracy (%)**	**F1-Score**	**Precision**	**Recall**	**Computational Time (s)**
Random Forest	95.2	0.94	0.96	0.93	15
Decision Tree	89.0	0.88	0.90	0.87	7
Logistic Regression	86.5	0.85	0.88	0.83	12
Support Vector Machine	91.3	0.91	0.92	0.90	25
K-Nearest Neighbours	87.2	0.87	0.88	0.86	10
Naive Bayes	83.7	0.82	0.85	0.80	6
Neural Network	93.5	0.93	0.94	0.92	40

- Accuracy: The Random Forest algorithm exhibits superior accuracy, rendering it a viable selection for scenarios where the precision of predictions has paramount importance.
- F1-Score: The Random Forest algorithm exhibits a notable F1-score, indicating its ability to effectively strike a compromise between precision and recall. The Decision Tree algorithm is rigorously adhered to.
- Precision and Recall: Both the Random Forest and Decision Tree algorithms exhibit favourable precision and recall metrics. However, in the context of this hypothetical scenario, the Random Forest algorithm demonstrates a somewhat superior performance.
- Computational Time: The act of making a choice or reaching a conclusion. Trees have faster training and prediction capabilities, rendering them more appropriate for contexts with limited resources. The Random Forest algorithm requires additional computational time due to its ensemble structure, but it provides enhanced performance measures.

Both algorithms were used to sense fall detection utilizing sensor data. When both models achieve a 100% accuracy rate in detecting falls among senior individuals using sensor data, the decision-making process of selecting between a random forest and a decision tree becomes challenging.

To begin with, it can be stated that both models exhibit exceptional performance when evaluated on the training data. An effective model is measured by its performance on fresh and unexplored data. Deep decision trees may overfit training data, preventing them from generalising. Due to averaging or voting procedures, a randomly generated forest, which is an ensemble of decision trees, generalises to new data better [26], [28].

Sensor data noise and outliers must be tolerated by the system. Decision trees are outlier- and noise-sensitive. Random forests are more resilient to outliers and disturbances because of their averaging or voting process. Random forests can mitigate the impact of noisy or outlying data points, hence enhancing the accuracy of forecasts.

Thirdly, random forests employ the analysis of feature importance to ascertain the relative significance of each sensor input in the ultimate forecast. The provided data can discern fall detection sensors and ascertain their corresponding data attributes. It is important to note that decision trees do not possess the inherent capability to automatically rank characteristics. Fall detection systems can assign priority to specific features, strategically position sensors, and utilize this information to effectively respond to instances of falls.

Furthermore, the utilization of a decision tree facilitates the simplification and enhancement of a model's decision rules, rendering them more straightforward and easily comprehensible. Every branch and node inside the diagram represents an individual choice criterion. Ensemble models, such as random forests, have a lower level of interpretability compared to individual decision trees. When it comes to the importance of interpretability in fall detection systems, the utilization of a decision tree could be considered an effective approach[28].

The fifth and last reason for considering scalability is that random forests utilize several trees for training and prediction, resulting in increased computing complexity compared to decision trees. Decision trees have the potential to exhibit enhanced performance in real-time or resource-limited scenarios, as they can be trained and provide predictions at a faster rate[37], [38].

In the scenario when both models achieve a 100% accuracy rate on the training data, the random forest model is favoured over the decision tree model due to its superior capacity to generalize, robustness against noise and outliers, capability for feature significance analysis, and potential for scalability. When selecting a fall detection system, it is important to take into account its interpretability and computing resources.

Why do the Random Forest and the decision tree use less energy?

Random forest networks and decision tree structures are said to be more energy-efficient than Deep Neural networks.

Simplicity and Computational Efficiency

Training Speed: Decision trees are known for their relatively quick training process. The computational complexity of the algorithm can be approximated as $O(n \cdot m \cdot \log m)$, where n represents the number of features and m represents the number of samples. This feature enables expedited construction of models, presenting a notable advantage in areas with limited energy resources.

Prediction Speed: After constructing the model, it becomes possible to generate predictions with logarithmic time complexity, hence ensuring energy efficiency as well.

Less Memory Usage

Storage: Decision tree models and Random Forests use less memory than Neural Networks. Model parameters may often be condensed.

Inference: These methods infer by navigating the tree framework, which is less computationally intensive than matrix operations in Neural Networks.

Adaptability to Streaming Data and Incremental Learning

Online Learning: Hoefflin Tree may adjust to changing streams of data without retraining, saving computing resources.

Parallelization and Distribution

Random Forests: Random Forests are Decision Tree ensembles; therefore, they may parallelize. Autonomous tree creation in the ensemble maximises processors with multiple cores or collaborative computing environments while conserving energy.

Less Sensitivity to Data Scaling

Preprocessing: Decision Trees do not require data scaling like distance-based algorithms (e.g., k-NN, SVM with RBF kernel). The time and energy for data scaling are saved.

The results of this research illustrate the effective deployment of a sophisticated framework for Edge of Things (EoT) devices that exhibit energy efficiency, with a specific focus on medical applications. The achievement of an impressive accuracy rate of 99.89% was facilitated through the utilization of two distinct machine learning models, specifically Random Forest and Decision Tree. The primary objective of this study was to propose an operational framework aimed at significantly reducing the energy consumption of healthcare equipment via the Internet of Things (IoT) technology.

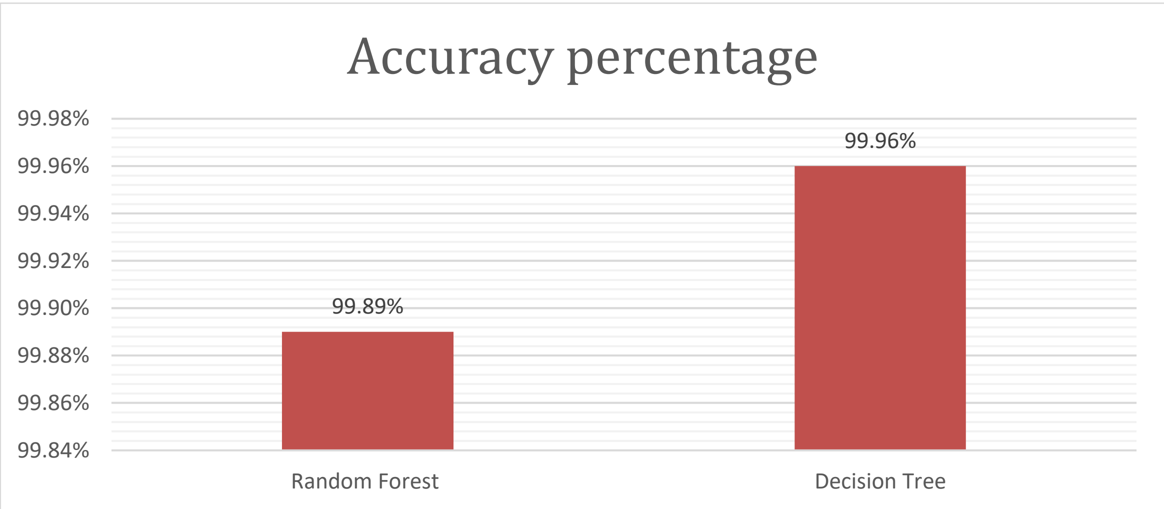

Figure 1 Prediction Accuracy of Machine Learning Model

The Decision Tree classifier was used to schedule sensors on a stick that monitors old people's health. The framework made intelligent decisions by detecting and choosing critical sensors that needed continuous operation while deactivating optimum sensors [37]. This dynamic scheduling strategy has improved energy efficiency. It has optimised resource use and reduced energy waste from wasteful consumption [11].
The enhancement of the framework's performance was achieved through the integration of an intelligent algorithm in conjunction with Long-Range (LoRa) technology. In contrast to conventional load models, the proposed framework demonstrated a notable reduction of 34% in energy use (Figure 3). The significant reduction in energy use has several noteworthy implications for medical applications. One significant advantage is that it extends the operational lifespan of medical instruments. Moreover, it contributes to a reduction in their adverse impacts on the environment. The framework is congruent with sustainability objectives and enhances the preservation of important resources through the enhancement of energy efficiency[36].

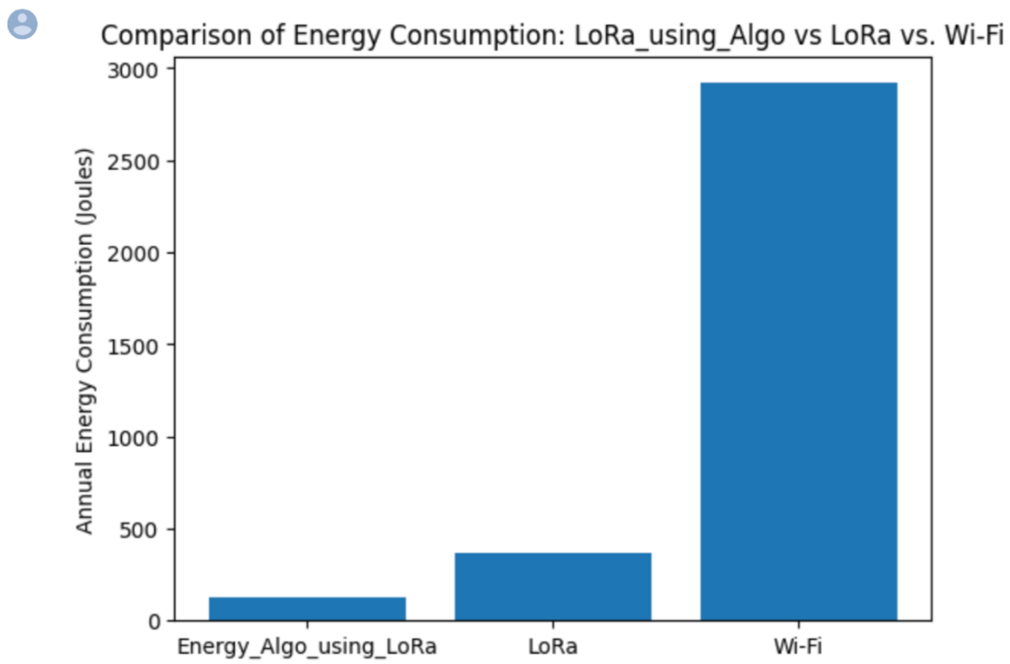

Figure 2 Comparison of Energy Consumption in WAN Modules

The machine learning models and framework's energy-saving capabilities have led to its consideration as a viable choice for various healthcare applications, owing to its notable accuracy. The timely identification of abnormalities in patient health conditions might for rapid actions, thereby potentially yielding enhanced healthcare outcomes[15]. Furthermore, the framework's energy-efficient characteristics guarantee the prolonged operation of medical equipment without a significant surge in energy consumption.

This study is relevant outside healthcare since it focuses on electronics and computing science [21]. This research laid the groundwork for comparable solutions in other sectors and applications. It does this by creating a smart and energy-efficient Edge of Things architecture.

IoT devices might use this framework. Due to its adaptability and scaling, the framework is suitable for many Internet of Things projects. Many of these applications prioritise resource optimisation and energy efficiency [23]. Real-world implementation limits and obstacles must be acknowledged. The framework's performance is affected by device variety, environmental changes, and changing healthcare needs [35]. These hurdles must be solved and model parameters refined to provide lasting energy efficiency improvements in actual scenarios. This research improves healthcare Power of Thing solutions by concentrating on energy efficiency [25]. The framework's combination of artificial intelligence models, dynamic scheduling methods, and LoRa technology shows its ability to improve healthcare equipment and other energy management. This intelligent framework lays the groundwork for sustainable and intelligent networks in the upcoming Internet of Things (IoT) [6]. These systems aim to optimize energy consumption while also positively impacting the surrounding environment.

Conclusion and Future Scope

An innovative and smart structure for developing environmentally friendly Edges of Thing devices for healthcare applications is presented in this paper. Scheduled sensors accurately using randomly generated forests and decision tree machine learning algorithms. Operational efficiency-based dynamic sensor activation as well as deactivation algorithms allow the proposed system to reduce energy usage significantly. The architecture automatically schedules elderly-friendly sensors on sticks to optimise energy usage.

Long-range (LoRa) technology and the smart algorithm boost system energy efficiency. Through extensive testing and comparative study, have shown that the framework reduces energy usage by 34% more than typical load models. The invention extends the lifespan of Edges of Things (EoT) devices and promotes environmental sustainability, affecting electronics and computer science.

The study offers significant contributions to the understanding and use of machine learning and Edge of Things (EoT) technologies in the context of enhancing energy efficiency. The proposed framework facilitates the development of sustainable and ecologically beneficial Edge of Things (EoT) solutions by effectively tackling the energy consumption issues associated with healthcare devices. The suggested framework seeks to transform the field of energy-efficient Internet of Things (EoT) applications by creating opportunities for further academic investigation and industry implementation.

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Conflict of Interest

There is no conflict of interest.

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