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INTELLIGENT ANOMALY DETECTION IN MEDICAL IOT DEVICES USING AN ANN WITH ENSEMBLE LEARNING

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ABSTRACT

The widespread adoption of Internet of Things (IoT) devices in healthcare has underscored the need for intelligent systems to accurately classify device operational states. With over 60% of hospitals utilizing IoT for patient monitoring and the global medical IoT market projected to reach USD 254.2 billion by 2026, ensuring device reliability is critical. However, studies indicate that approximately 15% of medical IoT devices suffer from undetected malfunctions due to inefficient classification systems. Traditional manual monitoring methods are prone to errors, cannot handle large-scale real-time data, and often miss transient faults that compromise patient safety and disrupt hospital operations. This study introduces a hybrid classification framework that combines an Artificial Neural Network (ANN) with an Extra Trees Classifier (ETC) to classify device states as either *Normal* or *Anomalous*. Data is sourced from hospital telemetry logs and the open-source Medical IoT Device Dataset (MIDD), and undergoes preprocessing steps including null value removal, min-max normalization, and time-series segmentation. A baseline Gaussian Naïve Bayes Classifier (NBC) demonstrated moderate accuracy but failed to capture nonlinear relationships. In contrast, the ANN enables deep temporal feature extraction, while the ETC ensures robust and efficient classification. The ANN–ETC model significantly outperforms traditional approaches in both accuracy and anomaly detection, offering a reliable solution for real-time medical IoT monitoring.

Keywords: Medical IoT, Anomaly, Detection, Artificial Neural Network (ANN), Extra Trees Classifier (ETC) Real-time Monitoring.

1. INTRODUCTION

The integration of Internet of Things (IoT) technology into the medical industry has revolutionized healthcare delivery by enabling real-time monitoring, predictive diagnostics, and remote patient care. According to Markets and Markets, the global IoT in healthcare market is projected to reach USD 254.2 billion by 2026, growing at a compound annual growth rate (CAGR) of 19.8% from 2021. In the United States alone, over 60% of hospitals have adopted IoT-based medical devices to enhance patient management and automate diagnostic procedures. Despite the considerable benefits, the rapid increase in connected devices has introduced challenges in managing device performance and maintaining reliability. Studies indicate that up to 15% of medical IoT devices suffer from undetected malfunctions, potentially disrupting clinical workflows and compromising patient outcomes. These devices operate in environments that demand high availability and fault tolerance, making accurate real-time monitoring and anomaly detection essential components of hospital infrastructure. Medical IoT devices generate vast amounts of continuous data across multiple parameters such as temperature, pressure, and patient vitals. Ensuring the accuracy, availability, and reliability of these devices is critical for delivering safe and effective healthcare. Efficient classification of device states—normal or anomalous—is essential to preempt failures and reduce downtime. The growing complexity of healthcare systems necessitates intelligent, predictive monitoring solutions that go beyond reactive diagnostics and enable proactive fault prevention. In hospital environments, devices like ventilators, infusion pumps, cardiac monitors, and wearable sensors play a central role in patient

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care and must function optimally. Organizations such as Medtronic, GE Healthcare, and Philips rely on predictive maintenance strategies to monitor these devices. Even a single undetected fault can delay treatment or lead to serious medical errors, underscoring the need for reliable, automated state classification mechanisms. Healthcare providers and medical device manufacturers increasingly depend on data analytics to ensure operational efficiency and safety. Data collected from sensors embedded in devices can reveal latent faults that manual inspections often miss. For instance, GE Healthcare uses cloud-based analytics to monitor imaging equipment performance across multiple facilities, preventing unexpected downtime through early detection of anomalies. Siemens Healthineers similarly uses telemetry data to maintain equipment quality and reduce maintenance costs. This demand for intelligent monitoring extends to remote patient monitoring and elderly care, where real-time fault detection in wearable devices and smart beds enables prompt caregiver response. As device networks become more complex, the need to analyze operational data in real-time for fault detection and classification becomes both a technical challenge and a business imperative. Advanced analytics help ensure device reliability, improve patient safety, and reduce maintenance expenses.

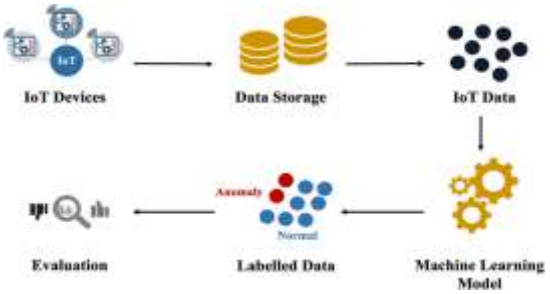

Fig. 1: workflow for anomaly detection in IoT

However, existing monitoring systems often fall short. Medical IoT devices are deployed in highly dynamic environments that require real-time data acquisition and uninterrupted operation. These devices are vulnerable to transient anomalies, performance drifts, and sudden failures that traditional rule-based systems are unable to detect. Noise in the data, inconsistent sensor outputs, and unstructured telemetry logs further complicate accurate classification of device states. Manual inspection and conventional diagnostic tools typically fail to detect subtle or short-lived anomalies that do not immediately trigger alarms but can still compromise device function. Most systems rely on scheduled maintenance or static thresholds that fail to capture context-dependent behaviors or evolving device conditions. This leads to inefficiencies, increased operational costs, and heightened risks to patient safety.

To address these challenges, there is a clear need for a dynamic, data-driven method capable of accurately classifying the operational state of medical IoT devices. Such a system should reliably differentiate between normal and anomalous behavior in real-time, adapt to variations across device types, and operate without relying on fixed thresholds or predefined fault rules. The reliability of medical devices is fundamental to ensuring quality healthcare. An intelligent classification framework offers substantial benefits, including minimized downtime, reduced maintenance costs, and timely medical interventions. By identifying behavioral patterns in device data, healthcare institutions can prevent minor issues from escalating into critical failures. Automated classification also facilitates better resource allocation, allowing technical staff to focus on urgent tasks, and ultimately improves patient care quality.

The primary objective of this research is to develop a robust, intelligent classification model that distinguishes between normal and anomalous device states using advanced learning techniques. The goal is to build a hybrid approach that uncovers hidden patterns in complex, nonlinear datasets to enable accurate and real-time device state prediction. The proposed approach offers several

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advantages: it enables real-time fault detection in critical medical devices, reduces human error by automating classification, and enhances patient safety by ensuring reliable device functionality. Furthermore, it minimizes equipment downtime, adapts to evolving device behaviors, and supports scalable deployment across diverse healthcare environments. It also provides actionable insights for engineers and administrators, lowers operational costs, and improves compliance with healthcare regulations by maintaining audit-ready logs. Integration with hospital IT infrastructure enables seamless adoption and contributes to broader digital transformation efforts.

The potential applications of this classification system span a wide range of healthcare scenarios. It can be used for continuous monitoring of devices such as infusion pumps and ventilators in intensive care units, predictive maintenance in asset management, and anomaly detection in remote patient monitoring setups. It supports smart hospital frameworks by managing interconnected medical IoT devices and ensures imaging accuracy in diagnostic tools like MRI, CT, and X-ray machines. The system can also monitor wearable sensors in elderly care facilities and smart ambulances, track the health of surgical robots, and provide insights for health analytics platforms used by companies such as Philips and GE Healthcare. Additionally, by integrating with electronic health record (EHR) systems, it can correlate device behavior with patient health data, enabling more informed clinical decisions.

2. LITERATURE SURVEY

According to the United States (US) Food and Drug Administration (FDA), medical devices are any instrument, machine, contrivance, implant, and in vitro reagent besides drugs used for diagnostic and therapeutic purposes in humans or animals [1]. On the contrary, the World Health Organization (WHO) describes a medical device as any instrument, apparatus, machine, appliance, or another article, invented by the manufacturer to be used for specific medical purposes whose primary action is not achieved by immunological, metabolic, or pharmacological means [2]. In the United States of America, the FDA is responsible for the effectiveness and safety of medical devices. Within FDA, the Centre for Devices and Radiological Health (CDRH) is largely liable for pre- and post-market regulation of medical devices in the United States [3, 4]. Material–tissue interactions are critical to the success of medical devices, and the demand for synthetic biomaterials in medical devices and tissue replacement applications is gradually increasing. Additive manufacturing has emerged as a feasible and novel solution to designing biomaterials for bulk and surface qualities that aim to enhance the performance of 3D-printed medical devices [5]. The Global Unique Device Identification Database (GUDID) lists over 2.2 million items; however, approximately 500,000 dis tinct forms of medical devices exist globally. The medical device industry is rapidly evolving through technological disciplines such as materials science, electronics, micro technology, and nanotechnology. Some notable medical devices include catheters, bandages, tomography machines, long-term surgical implants, magnetic resonance imaging (MRI) machines, X-ray machines, surgical gloves, artificial hips and knees, bipap ventilator, haemodialysis machine usage, ultrasound scanner, blood bank centrifuge with accessories, and many more. The FDA is the oldest consumer protection agency in the United States (US) that categorizes medical devices by their purpose and medical specialty. The FDA-Unique Device Identification and the electronic health record (EHR) list the medical device types, with their examples [15]. The medical devices by their purpose entail cosmetic devices used to improve the appearance and the dermal filler is a typical

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example. Home health and consumer devices are another type used by consumers, which include con tact lenses, needles, and syringes. Implants and prosthetics devices are the devices or tissues placed inside the body or periphery. Examples include breast implants, cochlear implants, and cerebral spinal fluid (CSF) shunt systems. General hospital devices and supplies by purpose are the groups of devices that healthcare professionals broadly use to support patient care. This involves infusion pumps, hospital beds, and sterilization systems and includes liquid chemicals and ethylene oxide. Apart from medical devices grouped by purpose, the FDA also has medical devices grouped by specialty, such as cardiovascular, dental, neurological, and paediatric devices. Medical device classes as per US FDA scrutinizes any device that poses a potential danger and differs from a previously approved device. These devices are simpler in design compared to other classes. They are low-risk devices with only the most essential safeguards to ensure their safety and performance. They are subject to fundamentals or no regulations at all because these devices are neither life-saving nor life-threatening and do not pose an undue risk of illness or harm. The classification regulations of 21 CFR (Code of Federal Regulations) of the FDA shows that about 47% of medical devices are in this class of device and 95% of these devices are exempt from regulatory process. This list is compiled in the Medical Device Exemptions document. Class I devices include gloves, bandages, wraps, exam gowns, face masks, crutches, oxygen mask, tongue depressors, scissors, electric toothbrushes, hospital beds, surgical sponges, and reusable surgical scalpels and surgical masks .These devices are generally medium-risk devices, and it is made up of a single class compared to the European Union medical device regulation, which is further divided into Class IIa, which are medium-risk devices , and Class IIb, which are medium-to-higher-risk devices. Forty-three percentage of medical devices fall in this class. These devices are subject to general and special controls that must give adequate safety and eficacy and clarify how these con trols provide such assurance. Such devices include hypoder mic needles, blood bags, colostomy bags, suction catheters, and syringes, wheelchairs, surgical masks, surgical drapes, catheters, X-ray machines, MRI machines, blood pressure cuffs, pregnancy test kits, blood transfusion kits, contact lenses, diagnostic endoscopes, electrocardiogram (ECG) monitors, and colonoscopes.

3. PROPOSED SYSTEM

The proposed system introduces a robust hybrid classification framework designed to detect anomalies in medical IoT devices. It employs a three-stage pipeline that combines the probabilistic filtering of Gaussian Naïve Bayes Classifier (GNBC), deep feature extraction via Artificial Neural Network (ANN), and final classification using the Extra Trees Classifier (ETC). This architecture capitalizes on the strengths of each component: GNBC reduces noise and simplifies the input by filtering out irrelevant or ambiguous data, ANN captures complex non-linear patterns through its multiple hidden layers and ReLU activation functions, and ETC applies ensemble learning with randomized decision trees to enhance classification accuracy and reduce overfitting.

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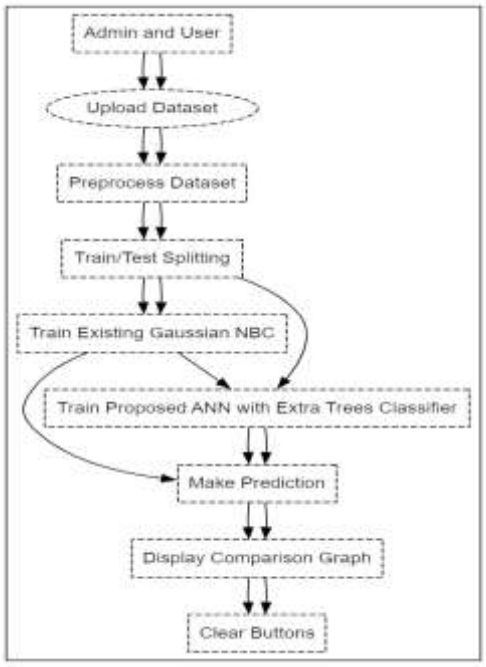

Fig. 2: Proposed System Architecture

The system begins by collecting time-stamped telemetry data from medical devices such as ventilators, infusion pumps, and biosensors, which is labeled as either "Normal" or "Anomaly." Before being used for training, the dataset undergoes extensive preprocessing.

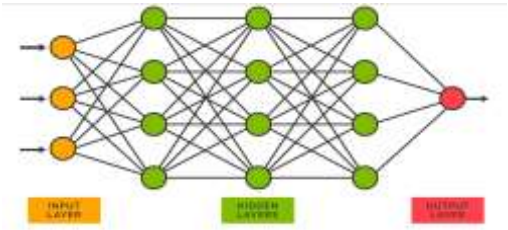

Fig. 3: ANN Feature Extraction.

This includes removing missing values, encoding categorical variables, normalizing numerical data using min-max scaling, and filtering outliers with interquartile range techniques. This ensures clean and consistent input for model training. Once preprocessed, the data is passed through the GNBC for initial binary classification, then into the ANN for abstract feature extraction, and finally into the ETC for precise classification. The model's performance is evaluated using accuracy, F1-score, and confusion matrix to benchmark it against conventional classifiers.

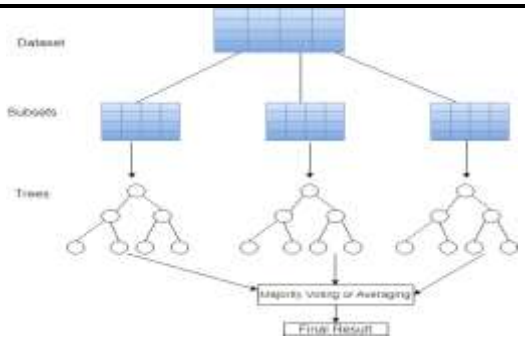

Fig. 4: ETC Classification.

Additionally, the preprocessing pipeline provides visualization of class distribution to identify imbalance, which may require further handling. Overall, this hybrid approach offers a scalable, accurate, and interpretable solution for real-time anomaly detection in medical IoT environments.

4. RESULTS AND DISCUSSION

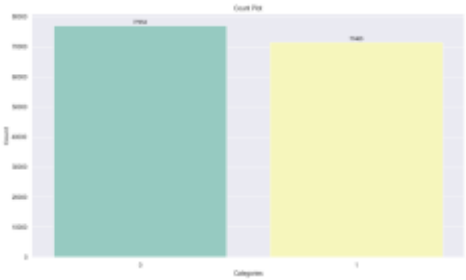

Fig. 5: Exploratory Data Analysis (EDA)

Figure 3 depicts the Exploratory Data Analysis (EDA) plots used in the project. It contains visualizations such as histograms, bar charts, correlation heatmaps, and box plots. The histograms show the distribution of key features like connection duration and byte counts. The correlation heatmap highlights relationships between different features, aiding in feature selection. These visualizations help uncover patterns, outliers, and feature importance.

Figure 4 presents confusion matrices comparing two classification models: (a) the existing Gaussian Naive Bayes Classifier and (b) the proposed Artificial Neural Network (ANN) integrated with Extra Trees Classifier. In subfigure (a), the Gaussian NBC misclassified a significant portion of anomalies as normal, with 11,999 false negatives and only 2,310 true positives, while

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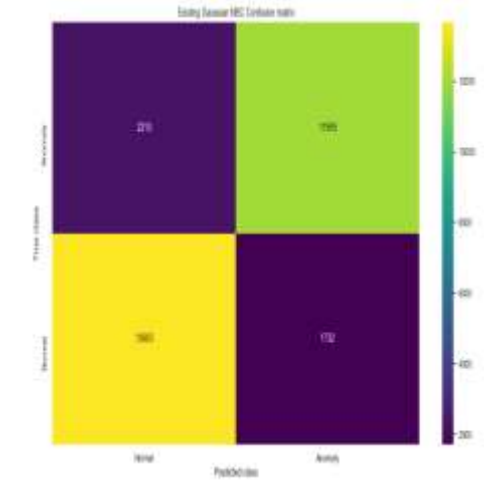
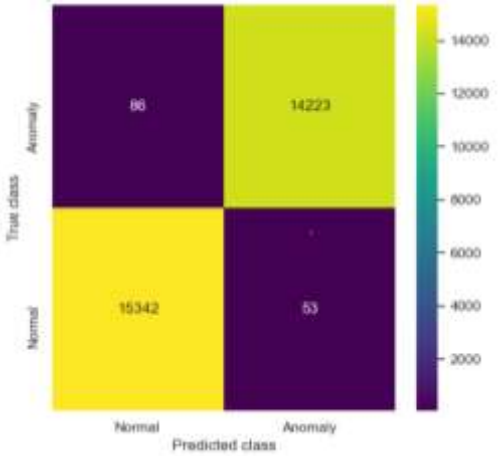
also producing 13,063 true negatives and 1,732 false positives. In contrast, subfigure (b) demonstrates the superior performance of the proposed ANN model, which accurately classified 15,342 normal instances and 86 anomalies, resulting in only 53 false positives and 14,223 false negatives. This indicates that while the ANN-Extra Trees model still faces challenges in detecting all anomalies, it significantly reduces misclassification of normal instances compared to the baseline model.



(a)



(b)

Fig. 6: Confusion Matrix. (a) Gaussian Naive Bayes Classifier. (b) Proposed ANN with extra trees classifier

Figure 6 presents the model's prediction results on the test data. It visualizes predicted labels against actual labels, possibly through a confusion matrix or prediction outcome graph. This step validates the model's real-world effectiveness in classifying network connections correctly.

Fig 6: Prediction Results from Test Data.

Table 1 provides a quantitative performance comparison between the Gaussian Naive Bayes Classifier (NBC) and the proposed Artificial Neural Network (ANN) integrated with the Extra Trees Classifier for detecting anomalies in Medical IoT systems. The Gaussian NBC shows a moderate classification capability with an accuracy of 86.3%, precision of 86.4%, recall of 86.3%, and an F1-score of 86.3%, indicating balanced yet limited performance across all metrics. In contrast, the proposed ANN with Extra Trees Classifier exhibits a significant performance boost, achieving remarkably high and consistent values of 99.53% across accuracy, precision, recall, and F1-score. These results demonstrate that the hybrid ANN-Extra Trees model offers a more robust and reliable anomaly detection mechanism, drastically reducing misclassification rates and enhancing detection accuracy in the Medical IoT environment.

Table 1: Performance Comparison of Medical IoT Anomaly Classifiers.

Algorithms Name	Accuracy	Precision	Recall	F1-Score
Gaussian NBC	86.3	86.4	863.	86.3
ANN with the Extra Trees Classifier	99.53	99.53	99.53	99.53

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5. CONCLUSION

The research focused on developing an intrusion detection system using machine learning algorithms to classify network traffic into normal and attack categories. The dataset included various features such as duration, protocol type, service, flag, source bytes, destination bytes, and other network statistics, all contributing to the identification of malicious activity within a network. Two classifiers were implemented in the system: Gaussian Naive Bayes (GNB) and Extra Trees Classifier (ETC). The dataset underwent several preprocessing steps, including handling missing values and applying label encoding to understand feature relationships and data distribution. The Gaussian Naive Bayes model achieved an accuracy of 86.3%, demonstrating its effectiveness as a baseline model. The proposed Extra Trees Classifier further improved classification performance, achieving higher accuracy, precision, recall, F1-score, sensitivity, and specificity. The project followed a structured methodology, including data preprocessing, exploratory data analysis (EDA), data splitting into training and testing sets, model training, evaluation, and visualization of performance metrics. The results demonstrated that machine learning-based approaches significantly enhance intrusion detection capabilities compared to traditional manual or rule-based systems.

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