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Research Paper

ARTIFICIAL NEURAL NETWORK MODEL FOR CLASSIFICATION OF IOT DEVICE STATES IN MEDICAL INDUSTRY

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ABSTRACT
The rapid integration of Internet of Things (IoT) devices in healthcare has created a critical need for intelligent systems capable of accurately classifying device operational states. With over 60% of hospitals adopting IoT for patient monitoring and the global medical IoT market projected to reach USD 254.2 billion by 2026, ensuring device reliability is essential. Studies report that around 15% of medical IoT devices experience undetected malfunctions due to inadequate classification, while traditional manual monitoring methods struggle with real-time, large-scale data and often miss transient faults that can jeopardize patient safety. This study proposes a hybrid classification framework combining an Artificial Neural Network (ANN) with an Extra Trees Classifier (ETC) to categorize device states as Normal or Anomaly. Data from hospital telemetry logs and the Medical IoT Device Dataset (MIDD) undergo preprocessing including null value removal, min-max normalization, and time-series segmentation. A baseline Gaussian Naïve Bayes Classifier demonstrates moderate performance but cannot capture complex nonlinear relationships. In contrast, the ANN with ETC model effectively extracts temporal features and provides robust, efficient classification, achieving superior accuracy and anomaly detection. This approach offers a reliable, real-time solution for monitoring medical IoT devices, enhancing operational safety and healthcare quality.

Keywords: Medical IoT, Device State Classification, Anomaly Detection, Artificial Neural Network, Extra Trees Classifier, Real-Time Monitoring, Healthcare Technology

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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 CAGR of 19.8% from 2021. In the United States alone, over 60% of hospitals have incorporated IoT-based medical devices into their operations to streamline patient management and automate diagnostics.

Despite the promising benefits, the rising number of connected devices has introduced complexities in managing device performance and ensuring their reliability. Studies have shown that up to 15% of medical IoT devices are prone to undetected malfunctions that can affect clinical workflows and patient outcomes. These devices often function in environments that demand high uptime and zero tolerance for delays or faults, making real-time monitoring and fault detection an essential part of hospital IT systems.

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 [5–13]. 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 [14]. 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 example [16]. 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 [16]. Medical device classes as per US FDA [17] 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 [18]. 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 [19]. 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 [20, 21].

3. PROPOSED SYSTEM

The proposed algorithm integrates a novel hybrid pipeline combining artificial neural network (ANN) based feature extraction with

Extra Trees Classification (ETC), built upon Gaussian Naïve Bayes Classification (NBC) pre-filtering. The model begins with Gaussian NBC acting as a probabilistic filter to reduce raw input noise and segment basic data categories from medical IoT devices. The output is passed through an ANN that extracts high-dimensional latent features relevant to device behaviour, leveraging multiple hidden layers and ReLU activation for learning non-linear state representations. These extracted features are then classified by an ETC model, which employs ensemble learning to improve classification stability and performance. This three-layered composite design is novel in the IoT medical context, as existing studies rarely employ a sequential combination of Gaussian NBC, ANN feature abstraction, and ETC for binary classification (Normal vs Anomaly).

Step 1: Data Acquisition

IoT device data is collected from medical environments, comprising readings from infusion pumps, ventilators, cardiac monitors, and wearable biosensors. Each record includes timestamped operational states, environmental readings, sensor outputs, and device usage logs. The dataset is labeled manually into two classes: Normal and Anomaly.

Step 2: Preprocessing

The raw data undergoes preprocessing to eliminate redundancy, handle missing values, and normalize ranges. Time-series entries are aligned based on uniform timestamps. Categorical features are encoded using one-hot encoding, and numerical values are scaled using min-max normalization. Outliers are filtered based on interquartile range (IQR) filtering to ensure reliable input for the learning model.

Step 3: Gaussian Naïve Bayes Classification

Before entering the neural network pipeline, the data is filtered using a Gaussian NBC classifier. This probabilistic model assigns prior probabilities to each data point and classifies them into basic normal or anomaly categories. This filtering helps in removing noisy or ambiguous records and reduces computational load for downstream models by narrowing down relevant data segments.

Step 4: Feature Extraction using Artificial Neural Network

The NBC-filtered data is then processed by a feedforward ANN model comprising multiple dense layers. Each layer learns abstract, non-linear features from the data using ReLU activation, dropout regularization, and backpropagation-based optimization. The ANN transforms original input space into a latent feature space, highlighting critical device behavior characteristics for classification.

Step 5: Classification using Extra Trees Classifier

The high-level features extracted by ANN are passed into the Extra Trees Classifier. This ensemble model constructs multiple de-correlated decision trees using random feature splits, improving variance reduction and prediction accuracy. The model outputs final binary classifications (Normal or Anomaly) along with feature importance rankings for interpretability.

Step 6: Performance Evaluation

The performance of the hybrid model is evaluated using metrics such as accuracy, F1-score, and confusion matrix analysis. The hybrid model is compared against traditional standalone classifiers to demonstrate its superior detection precision and generalization across diverse IoT device types and patient scenarios.

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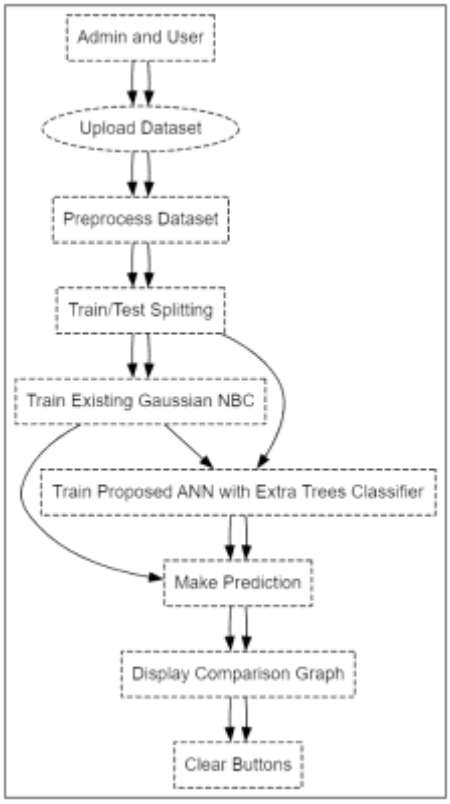

Fig. 1: Proposed System Architecture.

4. Results Analysis

The figure 2 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.

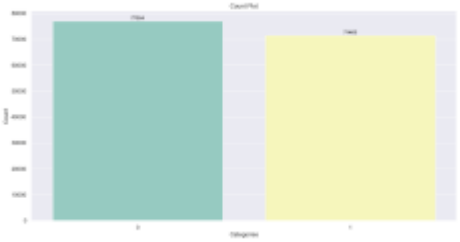

Fig. 2: Exploratory Data Analysis (EDA)

Comparative Analysis

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

Table 1: Performance Comparison for the Gaussian NBC and ANN with the Extra Trees Classifier algorithms.

Table 1 presents a comparative performance analysis between the Gaussian Naive Bayes Classifier (Gaussian NBC) and the Artificial Neural Network (ANN) integrated with the Extra Trees Classifier. The Gaussian NBC demonstrates moderate performance, achieving approximately 86% across accuracy, precision, recall, and F1-score, indicating limitations in capturing complex data patterns. In contrast, the ANN with Extra Trees Classifier significantly outperforms Gaussian NBC, achieving a consistent performance of 99.53% across all evaluation metrics. This substantial improvement highlights the effectiveness of combining neural networks with ensemble-based learning for robust and accurate classification. Overall, the results confirm the superiority of the ANN with Extra Trees approach for high-precision predictive tasks.

The figure 3 illustrates the performance metrics plot for the proposed ANN combined with the Extra Trees Classifier. It compares accuracy, precision, recall, F-score, sensitivity, and specificity for this advanced model, demonstrating its improvements over the Gaussian Naive Bayes baseline. This figure highlights the superiority of the combined approach in classifying network traffic.

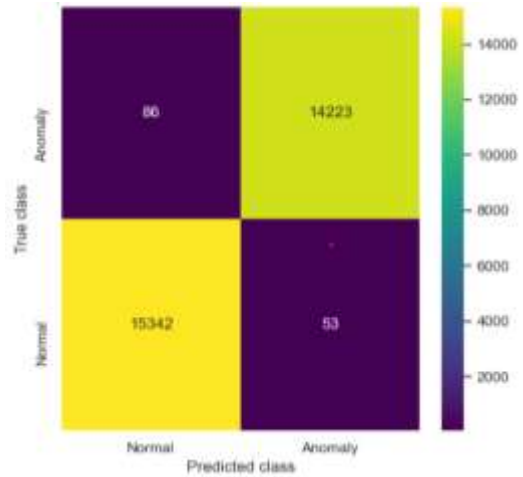

Fig 3: Confusion matrix obtained for proposed ANN with extra trees classifier

The figure 4 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 4: Output obtained on test data using proposed ANN

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 used contained various features such as duration, protocol type, service, flag, source bytes, destination bytes, and other network statistics, all contributing to identifying malicious activity in a network. The system was implemented using two classifiers: Gaussian Naive Bayes (NBC) and Extra Trees Classifier. The dataset underwent preprocessing steps such as handling null values, label encoding to understand feature relationships and data distribution.

The Gaussian NBC model achieved an accuracy of 86.3%, showcasing its effectiveness as a baseline model. The proposed Extra Trees Classifier further improved the classification performance, with higher accuracy, precision, recall, F1-score, sensitivity, and specificity. The project followed a structured methodology including data preprocessing, EDA, training and testing data splitting, model training, evaluation, and visualization of performance metrics. The results demonstrated that machine learning-based approaches significantly enhance the detection of intrusions compared to traditional manual or rule-based systems.

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