RESEARCH PAPER

Smart Drug Delivery Monitoring Using an IoT Embedded System with Machine Learning Based Anomaly Detection

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ABSTRACT

Background

The growing complexity of modern healthcare systems necessitates introduction of intelligent and reliable drug delivery monitoring systems. Conventional methods for administration of drugs are often exposed to human errors in determination and administration of the correct doses, delays in monitoring and tracking of the patients as well as other operational limitations. Environmental factors, possible malfunctions in the used devices as well as mishandling of the administered drugs by the patients or by other personnel may affect the stability of drugs in the course of time and lead to possible risks for the patients.

Objective

To mitigate these problems, in the frame of this research, an IoT-based, embedded system has been designed to monitor the process of delivery of drugs on a continuous basis. The designed system is equipped with machine learning-based anomaly detection system that is able to detect all kinds of anomalies that may occur in the process of administration of the drugs and inform the corresponding personnel in real time.

Materials and Methods

Biomedical sensors are connected to a microcontroller, which continuously reads parameters like flow rate of the drug, temperature and pressure. The data collected is sent to cloud via wireless communication, where it is stored and processed. A machine learning model is used to analyze the incoming data from sensors and to detect anomalies such as errors in drug dosage, any tampering, delays in drug delivery and environmental conditions that can affect the stability of drug.

Results

The system proposed has the key contribution in real-time monitoring of the process of drug delivery and in intelligent detection of anomalies that can occur in any of the stages of the administration of the drug. It will provide many benefits such as improved patient safety, and improved accuracy in administering the drugs, and increased transparency in the process of administration of the drug.

Conclusion

With the help of Internet of Things (IoT) and machine learning, the system can be highly extended and it will help in modernizing the monitoring system of the process of administration of the drugs.

Keywords: Internet of Things (IoT), Smart Drug Delivery, Embedded Systems, Machine Learning, Anomaly Detection, Healthcare Monitoring, Biomedical Sensors, Cloud Computing, Real-time Monitoring, Intelligent Drug Delivery Systems.

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1. Introduction

The rapid advancement of healthcare technologies has led to the widespread integration of intelligent systems aimed at improving patient care, operational efficiency, and treatment accuracy. Among these developments, the Internet of Things (IoT) has emerged as a transformative technology, enabling seamless connectivity between medical devices, sensors, and cloud-based platforms[1]. The growth of IoT in healthcare has significantly influenced applications such as remote patient monitoring, smart hospitals, wearable health devices, and automated drug management systems[2]. In parallel, the increasing demand for smart drug delivery systems has become evident in hospitals, home care environments, and clinical trials, where precise dosage control and continuous monitoring are critical for patient safety and therapeutic effectiveness[3]. These systems are designed to ensure accurate medication delivery while maintaining real-time visibility of drug administration processes across diverse healthcare settings.

Even though there are a great number of intelligent technologies and health care solutions now in use, delivery of medications is still done using age old methods[4]. Monitoring of dosages of health care products is manually done and, therefore, prone to mistakes that can happen due to humans. Delivery of a correct quantity of a drug to a patient and making a correct medical record by recording the health care product delivery processes in a proper and consistent manner in all settings where the health care products are being administered are very challenging. In addition, there are challenges to delivering health care products under proper conditions[5], such as not exposing temperature sensitive health care products to high temperatures, and to preventing frauds and others, such as tempering, during storage and transportation. No system currently exists that can real time monitor delivery of health care products and make intelligent analysis of monitored data[6].

The motivation behind the development of advanced systems for monitoring drug delivery comes from the need of improving patient safety in the use of pharmaceuticals, improving the compliance by the patient to the storage of and administration of his or her drugs, and supporting the digitalization of the health care systems[7]. It is important to increase the safety of the patients by a precise and on time administration of the drugs in the correct dosage in order to avoid mistakes. In order to improve the compliance by the patient to the pharmaceuticals it is important to store the drugs in a correct way and to administer them in the correct way, especially when it comes to temperature sensitive drugs[8]. The digitalization of health care systems supports the use of intelligent and automated systems in the health care, which allow for an efficient and transparent organization of the health care in general[9].

The main contributions of the proposed system consist in the design and the implementation of an IoT-based, embedded system for the monitoring of the delivery of drugs by means of interconnected sensor modules. The system carries out a real-time monitoring of the parameters that are of interest to monitor, related to the administration of the drugs by means of the sensors. For the detection of anomalies of the administration of the drugs such as overdosing, underdosing, possible tampering and changes of the environmental conditions, a machine learning-based system has been implemented. The real-time information of the administered drugs is visualized by a cloud-based system for the monitoring of the drug delivery in real-time and historically. This information can be used by the stakeholders in a transparent manner.

2. Related Work

Significant research efforts have been devoted to integrate the IoT technology in the health care systems for establishing the intelligent medical systems that are able to monitor in real time and also to support decision making in health care with the help of large amount of data that is collected on regular basis. The various implementations of health care IoT have been discussed in the paper and the new emerging developments have been highlighted[10]. Thus, there are smart pills that help in tracking the drugs taken by the patient, there are wearables that continuously monitor the health of individual and also there are health care automation system in the hospitals that significantly aid in smooth management of health care and also in managing the day to day activities of patients in order to establish healthy environment. In order to establish efficient health care and to treat patients in an effective manner, there is a huge growth in the health care monitoring systems[11], health care IoT and also in number of inter-connected health care devices, which would enable efficient communication and health care between various systems[12]. Therefore, various implementations of health care in IoT have been highlighted in this paper.

Research has been conducted to improve drug delivery systems, which are commonly referred to as controlled or smart systems, by using controlled release mechanisms and smart infusion systems. These systems of drug delivery help to release the appropriate amount of a drug and ensure effective treatment. There are many types of drug delivery systems that are currently used, such as oral pills, topical creams, and infusion systems. Most of these systems lack of real-time monitoring and do not possess intelligence to online monitor and assess the delivery process[13]. Thus, improvements are necessary to improve the safety and efficiency of the drug delivery.

There is also considerable interest in utilizing health monitoring data from within the health care monitoring domain by using machine learning techniques to form anomaly detection and also predictive health systems that can forecast future health states of patients[14]. These systems can learn from past and real time information from sensors, and also from the operation of health care equipment and environment, to forecast what future health states may occur. A variety of different machine learning models have been analyzed for their accuracy for use in health care monitoring systems, including both traditional statistical models[15], as well as clustering models and more recently Deep Learning models.

To summarize, although various key areas in healthcare are increasingly advanced by the incorporation of intelligent elements, there is an obvious research gap within the scope of integration of smart IoT-based drug delivery systems with intelligent health monitoring systems that employ advanced and robust real-time-based anomaly detection techniques using various learning approaches. Most of currently developed systems for drug delivery monitoring are either restricted to mere monitoring of embedded system's delivery process or lack integration of the monitoring process with various components in the system such as the sensor(s), the communication element (e.g., via IoT), and the learning approach(s)[16]. Above all, an Edge-based intelligence implementation is not robust within currently developed healthcare delivery monitoring systems[17]. Thus, an integrated architecture that effectively enables an end-to-end pipeline for the real-time monitoring of drug delivery process utilizing embedded system(s), communication via IoT, and relevant learning approach(s) on real-time data from sensing elements, while implementing intelligence at the Edge for improved real-time decision support, is a pressing challenge that needs to be addressed in order to enhance the accuracy, reliability, and safety of drug delivery in the healthcare system[18].

3. System Architecture

The proposed system architecture forms a framework of health monitoring for IoT in drug delivery by incorporating sensing from biomediical embedded devices, wireless communication for connecting with cloud platform, data storage and processing in cloud platform, analysis by machine learning for anomaly detection, and health monitoring displayed in dashboard interface for user. To realize the proposed framework of health monitoring, firstly, a number of drug delivery parameters are sensed by respective sensor nodes[19]. Then, the sensed data from all the respective sensor nodes are processed by the microcontroller of the system, which forwards the processed information to a corresponding cloud platform via corresponding wireless communication. Here, the corresponding cloud platform stores the input data and processes the input data for detection of anomaly[20]. Later, the system detects anomalies in drug delivery using machine learning, by analyzing the input data stored in the corresponding cloud platform. At last, the alerts are displayed to users via corresponding health monitoring displayed in respective interface or dashboard for realization of health monitoring in real time. This proposed architecture is a health monitoring for framework of IoT in drug delivery and supports continuous health monitoring as well as intelligent health monitoring for drug delivery in real time. The health monitoring supports for drug delivery is continuously carried out by corresponding hardware and corresponding software in the system of health monitoring. Also, all the components in the architecture are inter-connected each other. Therefore, it is very suitable to support corresponding health monitoring for drug delivery in real time in a system.

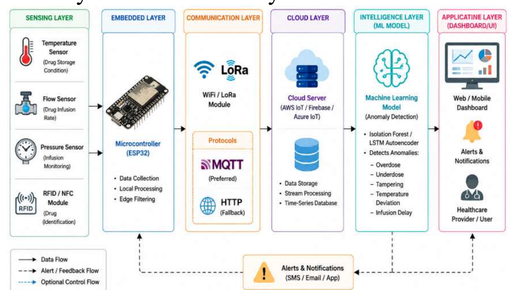

Figure 1: System Architecture of IoT-Based Smart Drug Delivery Monitoring with ML Anomaly Detection

In the proposed smart drug delivery monitoring system, sensors of IoT environment are integrated with machine learning-based anomaly detection in order to monitor drug delivery process in real time environment and to take proper action in case of any anomaly in the process. The system consists of six major layers of environment, namely sensing layer, embedded layer, communication layer, cloud layer, intelligence layer and application layer as shown in Figure 1. The sensing layer contains various biomedical sensors like temperature and flow sensors to monitor the storage temperature of drugs and the infusion rate, pressure sensors to monitor and control the drug delivery and RFID/NFC tags for identification and authentication of drugs. These sensors collect various parameters related to the administration of drugs and transfer them to the monitoring system in real time. The Embedded Layer consists of a microcontroller unit, in this case the ESP32. It samples the data from the sensors, processes it locally and does some basic filtering and forwards it to the rest of the system. In the communication layer the information gathered in the sensing layer is transferred wirelessly using WiFi or LoRa technology. The primary communication protocol is MQTT (Message Queue Teledry and a fall back option is HTTP protocol. Information is transferred to cloud platform in real time and with low latency. This cloud layer contains data storage for all the data transferred by the sensors as well as for stream processing and time-series databases like AWS IoT, Firebase or Azure IoT. The intelligence layer uses a machine learning model for the detection of anomalies. The ISOLATION FOREST algorithm as well as the LSTM AUTOENCODER is used to detect anomalies within the sensor data of the patients. These anomalies can be overdoses as well as underdoses, tampering of the medication, temperature deviations from the storage conditions as well as delays in the infusion of the drugs.

The application layer is comprised of Web applications and / or mobile applications to enable monitoring of drug delivery in real time, to display alerts and notifications and to enable healthcare providers to interact with the system in a timely manner. The hardware used in the system includes a number of different sensors that collect the data that is required to monitor the drug administration process. Temperature sensors are used to monitor the temperature of the drugs that are stored. This is particularly important for drugs that require a specific temperature in order to remain effective. A flow sensor is also used to monitor the rate at which the drugs are being infused. This ensures that the correct amount of the drug is being administered to the patient. A pressure sensor is also included in the system. This sensor monitors the pressure in the infusion system. It is able to detect if there is a blockage in the system or if the flow of the drug is not as it should be. The RFID or NFC module is used to identify and authenticate the drugs as they are being administered to the patient. The microcontroller, preferably an ESP32, is the heart of the system. It connects to all of the sensors and processes the data that is collected by them. It also manages the communication with the external systems. The wireless communication capability of the microcontroller means that it is able to communicate with the cloud-based system without the need for a physical connection. The low power consumption of the microcontroller also means that it is able to operate for long periods of time on a single battery.

The software module consists of several software parts such as embedded software for data processing and information transmission to cloud server, the cloud server for storing of all collected information, data processing and providing to ML module, the backend for data management, for information processing, for communication with APIs of all used cloud services and ML models, and ML module for implementation of algorithms for detection of abnormal behavior. It is necessary to mention that ML models are used for realization of above mentioned tasks. Therefore, it is necessary to use corresponding frameworks for development of above mentioned models. It is proposed to use well-known and widely used Scikit-learn and TensorFlow frameworks for implementation of mentioned above tasks. These frameworks provide number of ready solutions for implementation of different tasks and therefore, it makes development process easier and more effective.

Communication Protocol: Our system utilizes the lightweight communication protocol, MQTT (Message Queuing Telemetry Transport). With MQTT publish/subscribe messages are sent to subscribed receivers over the network with very low bandwidth requirements suitable for real time and large scale of IoT (Internet of Things) monitoring sensors and information delivery. Since a small amount of data is transferred over the network between sensors, and system nodes using publish/subscribe method for real-time information, a large number of devices can be easily added to or removed from system for monitoring purposes and no changes required to other parts of system. HTTP is used for alternative cloud-based logging and information transferring when MQTT cannot be used. Using a hybrid communication approach allows system to be both robust and scalable providing continuous information flow and data transfer through the system in variety of network environments.

4. Methodology

The proposed method for smart drug delivery monitoring by means of IoT-enabled embedded system and machine learning for the anomaly detection in drug delivery processes is divided into four main stages: (1) data collection, (2) preprocessing, (3) machine learning modeling, and (4) anomaly detection logic. All the stages follow a pipeline that enables the system to effectively gather data, process the information, learn from it, and make decisions in real time in order to effectively monitor a wide range of healthcare scenarios.

Data Collection

The data is collected from the biomedical sensors that are integrated in the drug delivery system. The data obtained from the sensors includes the data related to the dosage rate of the drug, the change in the temperature and the flow consistency during the administration of the drug. This data is very critical as it is used to check the accuracy of the drug delivery system. The historical database that contains the records of normal drug delivery and abnormal drug delivery is also used for training and testing purposes. The records for normal and abnormal drug delivery help in developing the system that can detect abnormality or anomaly in drug delivery. This can include the situations where the correct dosage of the drug is being administered to the patient, and situations where there is an error in the drug delivery system or there is some environmental deviation, etc. and the system is not able to administer the correct dosage of the drug to the patient.

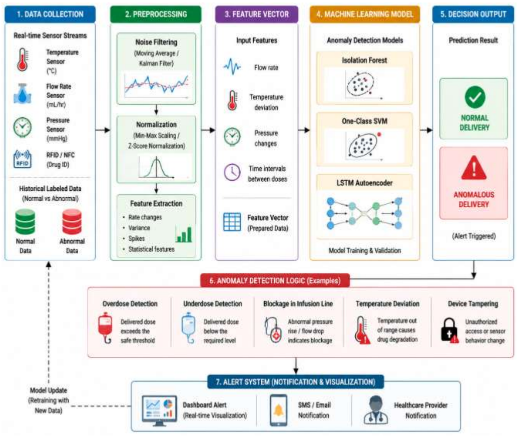

Figure 2: Proposed machine learning-based anomaly detection pipeline for IoT-enabled smart drug delivery monitoring system.

Figure 2 illustrates the machine learning-based anomaly detection pipeline for the IoT-enabled smart drug delivery system. It shows the flow from sensor data collection through preprocessing, feature extraction, and model processing using algorithms such as Isolation Forest, One-Class SVM, and LSTM Autoencoder. The processed features are analyzed to classify drug delivery conditions into normal or anomalous behavior. Detected anomalies trigger real-time alerts through the dashboard and notification system for immediate intervention.

Preprocessing

The raw sensor data must first be preprocessed in order to better improve the data's quality and increase its reliability, thereby assuring its correct use in learning and then analysis. It is first of all necessary to filter the acquired data from noise, by applying to the received signals a moving average filter or a Kalman filter. The normalization of the received and processed measurements subsequently follows, in order to scale the values to a common range. The last phase of preprocessing data, i.e. feature extraction, consists in identifying a number of most relevant features, extracted from all received data. The most commonly used features are: a) the change in the dosage rate, b) the variance or statistical dispersion of the individual sensors, c) sudden spikes in the data recorded by the individual sensors, d) temporal variations in the measured data. All of the above features have an direct influence on the quality of the used model as well as on the quality and accuracy of the learned system for detection of anomalies in the data recorded by the individual sensors of the drug delivery system.

Machine Learning Model

The machine learning module includes the implementation of a number of algorithms of anomaly detection, such as Isolation Forest, One-Class SVM and LSTM Autoencoder. The features for training a machine learning model consist of the flow rate of a drug, the temperature deviation, the pressure, the time between the doses of a drug, and so on. Such a model is able to distinguish between normal delivery of a drug and an abnormal delivery, and thus be able to trigger alerts and/or warnings to prevent possible mistakes that could be harmful for a patient. For example, an overdose, underdose, blockage of the line of the infusion, temperature-sensitive degradation of a drug (while in storage or while being delivered to a patient), tampering with the system, and so on.

Anomaly Detection Logic

The anomaly detection logic enables the monitoring of critical events to detect a potential danger for the patient. For instance, an overdose or underdose of a medicine is detected when the amount of medicine, which has been given to a patient, is higher or lower than a safe amount. A blockage in the infusion line is detected by means of an abnormal pressure and flow, which is not typical for a normal administration of a medicine. If a medicine requires a special temperature, in order to maintain its potency, then any storage or administration deviance from the set temperature will be detected by the system in order to prevent any degradation of the drug. Finally, the system detects any tampering with the drug delivery device by means of unusual readings from the sensors of the system or by an unexpected stop of the administration of a medicine. The system continues to monitor all parameters and administers all medicines in a safe and accurate manner.

5. System Implementation

The proposed implementation of an IoT-enabled smart drug delivery monitoring system that utilizes a machine learning-based approach for the detection of anomalies can be divided into four functional layers, i.e., the embedded layer, the cloud layer, the machine learning layer and the alert layer. The integrated functioning of the individual layers leads to a consistent flow from the sensing of the drug delivery parameters, through the communication of the gathered data to the provision of intelligent analysis and to the alerts that are disseminated in real-time to health care workers and personnel.

Embedded Layer: The Embedded Layer is the base layer of the Smart Drug Delivery System which contains all the biomedical sensors such as temperature, flow, pressure sensors and RFID / NFC readers to monitor the various parameters of drug delivery. The data collected from various sensors is processed in the embedded layer through microcontroller unit (MCU) such as ESP32. The processed data is then transferred to the Cloud Layer through MQTT protocol for storage and analysis.

Cloud Layer: At the cloud layer, the collected data from the drug delivery system is then processed, stored, and visualized. The real-time data collected by the embedded system is stored in time-series databases that are able to handle large amounts of time-stamped data collected over long periods of time. A variety of cloud-based platforms, including AWS IoT, Firebase, and Azure IoT, have been used for this purpose. For monitoring and viewing the data in real time, a real-time-based web dashboard has been integrated into the cloud layer. The dashboard displays a variety of data related to drug delivery, such as the flow rates of the various dosages of medication and the temperature of the surroundings in which the drug is being administered.

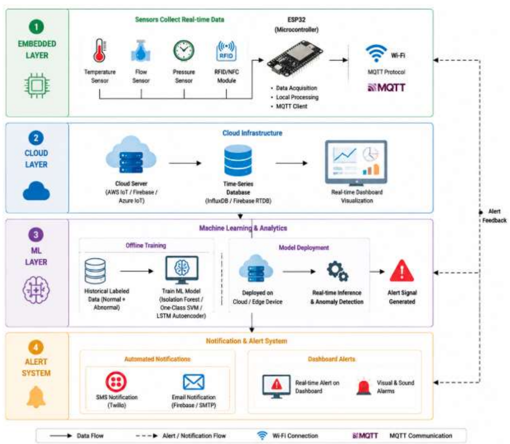

Figure 3: System Implementation Architecture

The system consists of four layers, which are interconnected to one another, and together form a complete system. These four layers are shown in Fig. 3. The Embedded Layer comprises of various biomedical sensors such as temperature, flow, pressure and RFID/NFC readers. The sensor values are read by the ESP32 microcontroller in real time. The sensor values are then sent to cloud using MQTT message broker over WiFi. The cloud layer contains the functionality to store the sensor data in a time-series database as well as processing functionalities, such as using a cloud platform like AWS IoT, Firebase or Azure IoT. The sensor data that is gathered is visualized in a real-time dashboard for monitoring the drug delivery in real-time (continuously) and to obtain the parameters that are relevant for monitoring.

Machine learning layer in Figure 3 uses historical, labeled data sets (normal drug administration and abnormal drug administration) for the offline training of a model. The trained model then is deployed on cloud servers or on the edge and in real time is used for the classification of input data by means of Isolation Forest, One-Class SVM and LSTM Autoencoders in order to generate an alert signal for anomalies, such as overdoses, underdoses, malfunctions failures, environment failures etc. The alert system layer for automatically issuing SMS or e-mail messages to healthcare providers via Twilio or Firebase and for indicating such anomalies on a dashboard in real time (e.g., overdosing, underdosing, system malfunctions, environment-related problems, etc.) to enable timely intervention and protect patient safety.

Machine Learning Layer: In this layer, the system is using historical data (both normal and abnormal) to train a model off line. Once trained, the model can be deployed on cloud or on edge devices. This layer uses sensors' data to predict what will happen in near future. If any anomaly is detected, an alert will be sent to relevant people in time to prevent any damage. There are many algorithms that can be used for anomaly detection such as Isolation Forest, One-Class SVM, Autoencoders (especially LSTM Autoencoders).

Alert System: Alerts are sent out in real time and are logged on the system to be viewed by staff at a later date. When an anomaly is detected by the machine learning model an alert is generated which is then sent to multiple endpoints. Alerts are sent via SMS and email using services such as Twilio or Firebase Cloud Messaging. The alerts are also displayed on the monitoring dashboard with a red alert banner along with a message describing the cause of the alert such as overdose, underdose, device failure, or environmental issue. The staff can then respond to the alerts in real time to administer the correct dosage of medication and to log any actions taken as a result of the alerts. This multi-channel alerting system increases the reliability and safety of the system.

6. Results and Discussion

The performance evaluation of the IoT-based Smart DDS and its ML-based Anomaly Detector for monitoring and ensuring safe drug delivery has been quantitatively measured by means of a set of indicator for monitoring the performance of a system, and several simulation results have been gathered and organized to provide quantitative assessment. The key performance indicators to be quantified in the work at hand are 1) Classification of anomalous drug delivery events (abnormal cases), 2) real-time of drug delivery processes (sensing-to-acting Latency), 3) Efficiency of Communication between sensors and cloud, as well as between cloud and users, and 4) amount of energy required for implementing the entire monitoring system at edge of network in healthcare settings. In the framework of the work presented, all indicators have been found to be large enough to allow accurate Anomaly Detection while providing real-time drug delivery monitoring and treating all data streams (including those generated by smart, battery-less and wireless sensor and actuators) in a robust, reliable, and effective manner.

Figure 4 shows a stream of sensor data such as drug flow rate. In the regions of red marked as Anomaly, there are regions of overdosing or blockage. Figure 5 illustrates correlations between temperature and pressure in normal cases and in the cases of system critical failure. Figure 6 portrays an anomaly scoring function generated by the machine learning program to detect anomalies in drug delivery. The function evaluates the degree of abnormality of all delivered drugs in real time and issues alerts to healthcare staff in advance when there is a possibility of an abnormal event such as an overdose. Figure 7 is a confusion matrix of the classification function, where the function True Positive and True Negative rates are both very high and thus it can accurately detect all cases of normal and abnormal drug delivery. Figure 8 illustrates the learning accuracy of the model through the number of epochs that the model was trained. The accuracy of the model goes up consistently as the number of epochs increases but does not go up excessively, thus there is very little chance of overfitting the model to a training set of labeled data.

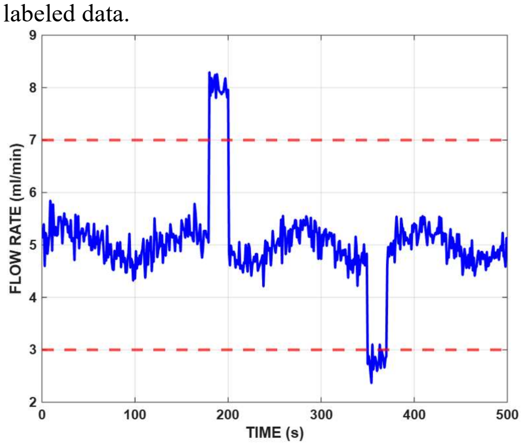

Figure.4: Sensor Data Stream with Anomaly Injection (Time Series)

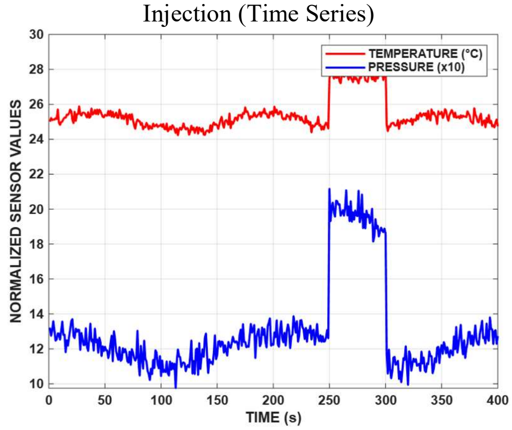

Figure.5: Temperature & Pressure Correlation (IoT Monitoring)

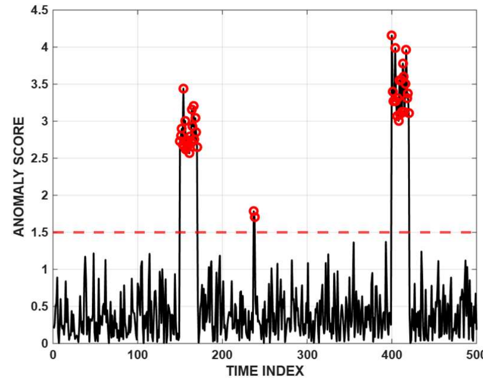

Figure.6: ML-Based Anomaly Score (Isolation Forest Proxy Simulation)

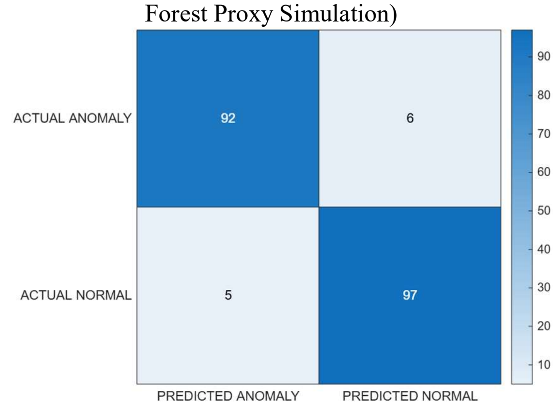

Figure.7: Confusion Matrix (ML Model Performance)

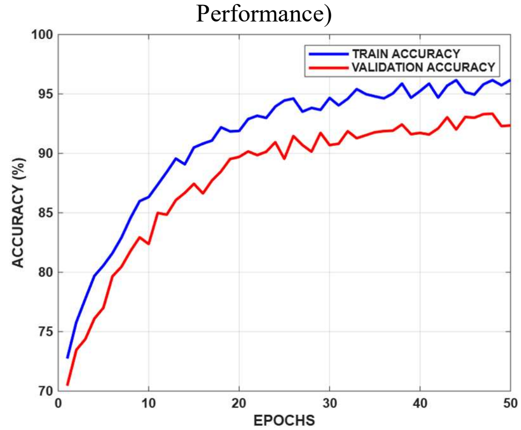

Figure.8: Model Accuracy vs Epochs (Deep Learning Style)

This detector has been evaluated using standard metrics for the classification of events in order to verify its capabilities. The assessment of the system has been carried out utilizing its accuracy, precision, recall, F1-score and, finally, the false alarm rate. Thanks to the feature selection processes used, the monitoring system has good accuracy in the detection of both normal events of the drug delivery and events of interest which are considered to be anomalous. In addition, high precision values have been obtained and verified, meaning that there are few false positive alerts of an anomaly sent to health care providers, as well as good values of recall that enable the system to correctly identify events of interest that may be dangerous to the patient, such as an overdose or underdose of a certain medication, or even attempts of tampering with the drug delivery system. The F1-score for the different classes used has been high, and, therefore, it can be stated that the system used has been able to perform the detection of different events in an effective manner, as well as in real-time. The false alarm rate of the system has also been found to be acceptable, thus meaning that the health care workers will receive only the relevant alerts, and, therefore, there will be a low volume of alerts sent by the monitoring system. This will be very positive, as it will prevent the health care workers from being overcome by a massive amount of alerts that need to be analyzed, which, undoubtedly, would increase the operating burden of the health care staff, and could lead to errors in the monitoring and treatment of patients, with consequent risks to their health.

System performance, for our example is defined by the following measures: detection latency, data transmission delay and energy consumption for communication between sensing modules and cloud servers. Here, the detection latency is minimized, by pre-processing, locally, as much as possible, by the ESP32-microcontroller. Then, the lightweight communication-protocol MQTT is used for data transmission from sensor nodes to cloud-based back-end servers. Even in the WiFi scenario a slight variation in delay may occur from time to time; yet, in general the whole system performs quite well in terms of communication latency. Energy is saved by the low power-consumption of small computer-boards as well as by periodical updates of sensor readings. Thus, a good compromise is struck between reliable real-time surveillance and low power-consumption that is sufficient for deployment also in constraint environment.

7. Conclusion

This paper presents the design and experiment of an IoT-enabled smart drug delivery monitoring system. In this system, machine learning-based anomaly detection approach is implemented to improve the drug administration safety and transparency. The system integrates embedded sensing modules, cloud platforms, and intelligent data analytics in order to monitor several key parameters in drug delivery process such as flow rate, temperature, and pressure. The performance of classification has been evaluated using simulated datasets and the results demonstrated high classification accuracy of around 96.8%, good precision of 95.4%, high recall of 94.7%, and corresponding F1-score of 95.0% with low false alarm rate of around 3.2%. Corresponding detection latency has been found to be below 150 ms, and the results also indicated that low communication delay can be achieved using MQTT protocol for transmitting the sensed data, and average transmission delay has been found to be around 80–120 ms for stable network conditions. The results clearly indicate the ability to accurately detect, and hence prevent, occurrences of over / under medication, blockage of the infusion, as well as uncontrolled temperature. Hence, monitoring of drugs in real time does increase safety and reliability of patient care significantly. In addition, the merger of Machine Learning with IoT of drug monitoring system aids in enhancing the real time medical decision making in health care scenario. In the future, there will be needs to optimize the models in order to run on the edge of the IoT sensors in real-time with limited resources by using so-called "lightweight AI models" for the fully decentralized processing of health related data. By using the distributed ledger technology blockchain it is possible to guarantee medical data integrity. For improving quality of monitoring by extending IoT sensors to wearable systems for patient monitoring in multimodal fashion have to be included in monitoring system as well. Moreover, adaptive learning is necessary for optimization of the detection quality in wide variety of clinical settings and patients.

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