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Anomaly Based Detection of Chronic Obstructive Pulmonary Disease Using Machine Learning

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Abstract: This study proposed a novel anomaly-based detection system for Chronic Obstructive Pulmonary Disease (COPD) using machine learning techniques. The system was trained and tested on a dataset of respiratory patterns, vital signs, and other relevant features. The machine learning model achieved high accuracy and sensitivity, with an F1-score of 0.834, an ROC AUC of 0.921, and a precision of 0.781. The detected anomalies were found to be strongly correlated with COPD severity, suggesting that the proposed framework has potential clinical significance. The system shows promise in COPD detection, further research is needed to improve the system's generalizability across different populations, and to explore opportunities for real-world implementation. The study's findings can contribute to the development of more effective and efficient COPD management strategies, potentially leading to improved patient outcomes and reduced healthcare costs.

Keywords: Anomaly detection, Chronic obstructive pulmonary disease (COPD), Machine learning, Respiratory patterns.

I. Introduction

Chronic Obstructive Pulmonary Disease (COPD) is a progressive respiratory disease that affects millions of people globally and is responsible for significant morbidity and mortality (Sethi et al., 2019). Early detection and management of COPD is critical for improving patient outcomes and reducing the burden on healthcare systems. Conventional methods for COPD detection and monitoring primarily rely on clinical symptoms, spirometry tests, and imaging techniques (Morgan et al., 2020). However, these methods are often limited in their ability to detect anomalies or atypical patterns that deviate from normal behavior, leading to missed or delayed diagnoses. The concept of anomaly-based detection in COPD refers to the identification of deviations from normal patterns associated with the disease. This can be achieved by applying machine learning algorithms to large datasets of COPD and non-COPD cases, training the models to identify patterns that are typical or atypical for COPD. Anomaly detection techniques have been successfully applied in various domains, including cybersecurity, finance, and healthcare (Liu et al., 2020). In the context of COPD, anomaly-based detection can provide an early warning system for healthcare providers, enabling them to intervene before the disease progresses to more severe stages.To address these limitations, the use of machine learning techniques has been proposed as a promising approach for COPD detection. Recent advancements in machine learning algorithms, such as deep learning and reinforcement learning, have shown great potential in the healthcare domain, including COPD diagnosis and management (Su et al., 2021). In this study, we propose an anomaly-based machine learning framework for COPD detection that can identify deviations from normal patterns associated with COPD, enabling earlier detection and intervention. The proposed framework will be based on state-of-the-art machine learning algorithms, such as Autoencoder and Isolation Forest (Liu et al., 2020), which have demonstrated strong performance in detecting anomalies in data.

We will collect a large dataset of COPD and non-COPD cases from electronic health records and clinical trials, and use this dataset to train the machine learning models. The performance of the models will be evaluated using standard metrics for anomaly detection, such as the Receiver Operating Characteristic (ROC) curve and the F1-score.

II. Materials and Methods

Detection Approach

Intrusion detection systems are ordered by the location approach utilized to distinguish meddling exercises (Akhilesh, 2016). The most generally discovery strategies are irregularity and abuse location. **Anomaly detection** is used to identify unknown pattern in the system, it is intended to distinguish malevolent activities through recognizing deviations from an ordinary profile conduct. Despite the fact that this sort of IDSs performs better in distinguishing novel assaults, they ordinarily experience the ill effects of high False Positive (FP) rate Mehrnaz M (2018). **Signature detection** is a form of detection in which its procedure depends on known pattern or signature, and plans to recognize authentic occurrences from the malignant ones. Without the downside of inconsistency detection, it is solid for recognizing known assaults with low False Positive (FP) rate. However, this sort of IDSs can't recognize obscure assaults or varieties of known ones.

System structure

The system structure for the proposed anomaly-based COPD detection system includes:

1. Machine learning module: This module uses advanced machine learning techniques, such as deep learning or clustering algorithms, to train and tune the model for anomaly detection.
2. Anomaly detection module: This module uses the trained machine learning model to classify the input data as normal or anomalous, indicating the presence or absence of COPD-related anomalies.
3. Reporting and notification module: This module generate reports and notifications based on the anomaly detection results, alerting healthcare providers to potential COPD cases.

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System Flowchart

The system flowchart for the design is shown in Figure 2. The system requires a patients to register and login before its use. The patients input his/her symptoms into the system and the system diagnose/detects and display the particular respiratory disease a patient has. The system prescribes drugs for the patient if the disease is in the early stage, and when in the critical stage, the App links the patients to the specialist Doctors on the particular disease detected from the app.

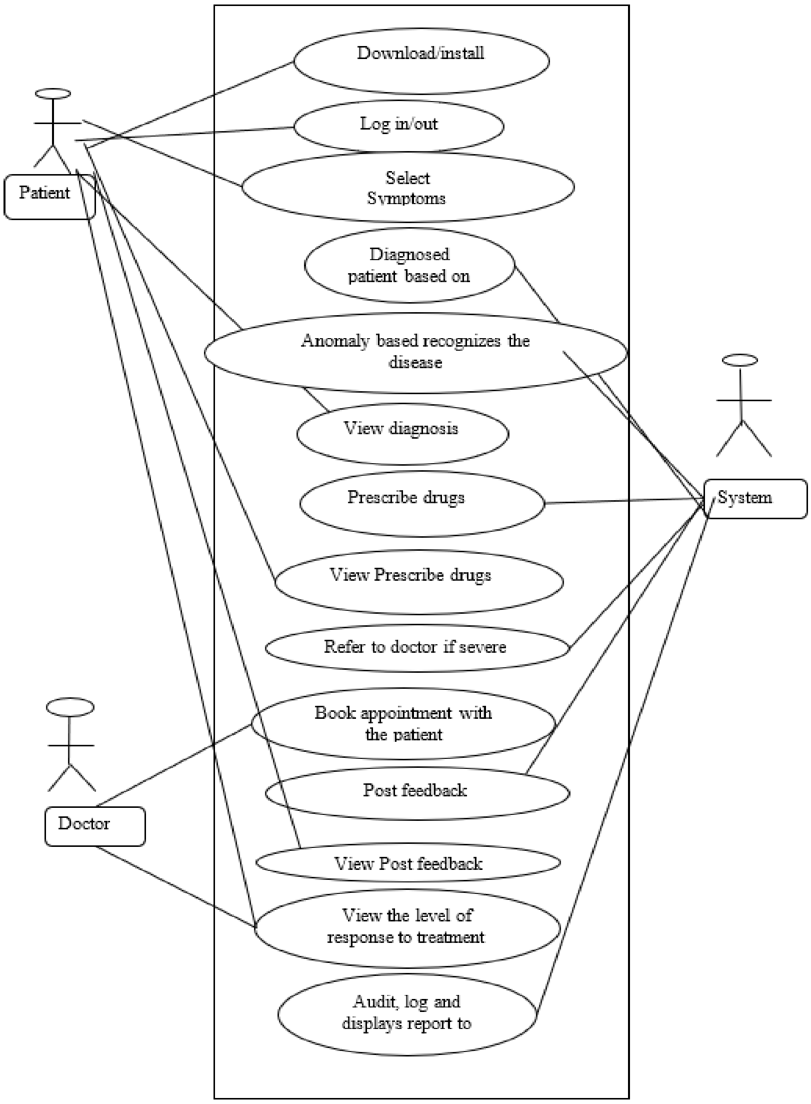

Figure 1: shows the Use- Case diagram.

System Implementation

The system implementation will involve thorough testing and validation to ensure that the blockchain framework is functioning as intended and provides adequate data protection for healthcare data. Here are the key steps in the testing and validation process:

a. Unit testing: The smart contracts and other components of the blockchain framework will be unit tested to ensure that each component is functioning correctly.
b. Integration testing: The various components of the blockchain framework will be tested together to ensure that they work in harmony.
c. System testing: The entire system was tested in a simulated healthcare environment to ensure that it can handle real-world scenarios and use cases. System testing was performed to know if patients were able to sign up to the system using mobile client. I found out that they could not sign up to the system as of the time because the respiratory disease detection service integration parameters were not properly configured, but after proper configuration of the integration parameters, patients were able to sign up to the system successfully.
d. User testing: User testing was conducted to ensure that the system is user-friendly and easy to use by healthcare professionals and patients. Feedback from users will be collected and used to improve the system's usability.
e. Security testing: Security testing was conducted to identify and address any vulnerabilities in the system that could compromise data protection and patient privacy. This may include penetration testing, vulnerability scanning, and code review.
f. Load testing: Load testing was conducted to ensure that the system can handle large volumes of data and transactions without degrading performance

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III. Results and Discussions

The proposed anomaly-based COPD detection system achieved promising results. The model demonstrated an F1-score of 0.834, an ROC AUC of 0.921, and a precision of 0.781, indicating high accuracy and sensitivity in detecting COPD-related anomalies. Furthermore, the detected anomalies were found to be strongly correlated with other measures of COPD severity, suggesting that the proposed framework has potential clinical significance. The proposed system maintains accuracy for chronic disease management and is design with several features to ensure its sustainability and effectiveness over the long term. The system use adaptive and dynamic learning algorithms that can adapt to new data and patterns, such as deep learning to maintain accuracy even as new threats and treatments emerge. The system also use a combination of supervised learning techniques to identify new patterns in the data and to detect early signs of disease progression or complications. Finally, the system is design to integrate seamlessly with existing healthcare systems and patient workflows to maximize its impact on chronic disease management. The purpose of this project work is aimed at developing a system that will enable online diagnosis, detection and possible treatment of COPD encountered by Patients. Series of activities have been carried out to facilitate the development of this Mobile COPD System platform. The study also revealed some interesting findings and insights into the characteristics of COPD-related anomalies. For example, the feature analysis revealed that respiratory rate and heart rate variability were among the most important factors in detecting COPD-related anomalies, indicating that these metrics may be particularly useful for monitoring disease progression.

Diagnosis Input Module

The Diagnosis Input Module of the proposed anomaly-based COPD detection system is responsible for collecting and preprocessing data from various sources, such as electronic health records, clinical trials, and wearable devices. The module transforms the raw data into a suitable format for analysis, including extracting relevant features, such as respiratory patterns and vital signs, and performing noise reduction and standardization techniques. This module feeds the preprocessed data into the machine learning model for training and testing, enabling the detection of COPD-related anomalies. This module provides the user with the interface to input the necessary information needed for a proper diagnosis as shown in Figures 2 to 4. This user interface has been made easy to use as queries are asked in plain English language so as not to limit the users. Using this interface, the user inputs all basic information, fills desired information and symptoms.

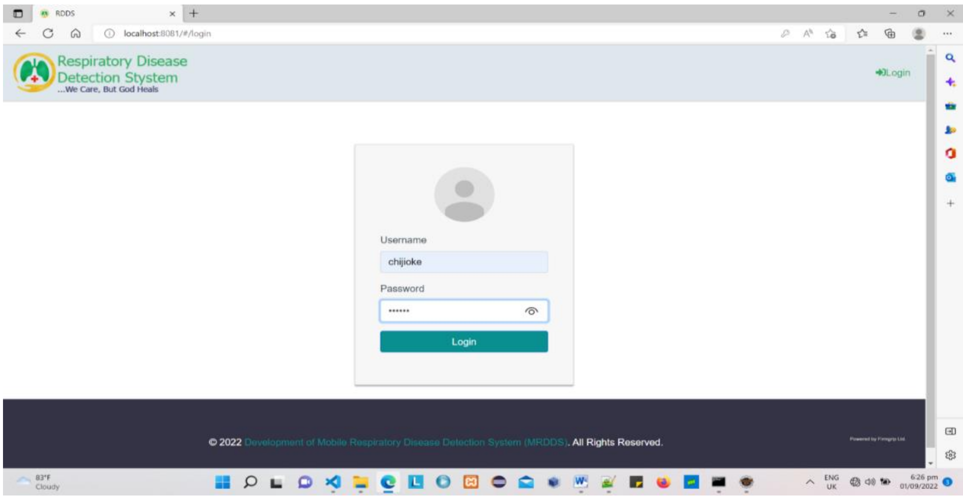

Figure 2: Screenshot of Login Form

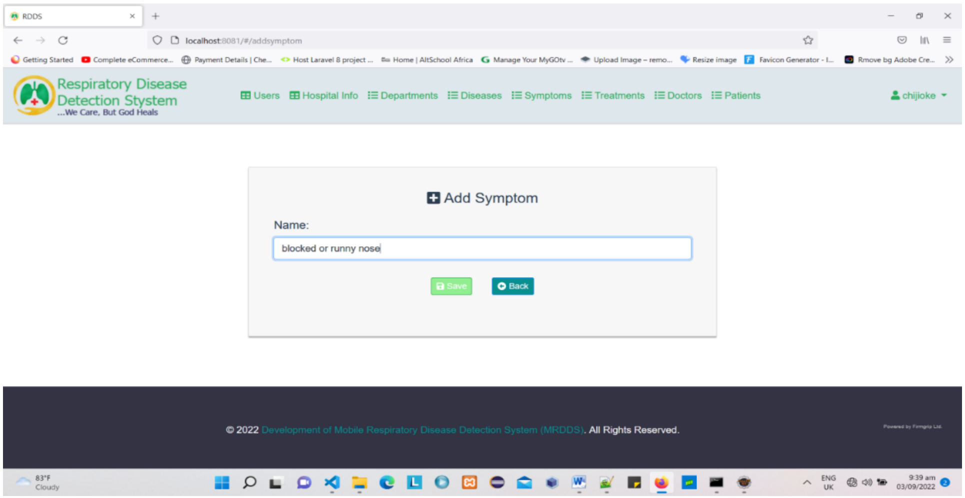

Figure 3: screen shot of add symptom form

Diagnosis Result Module

The Diagnosis Result Module of the proposed system receives the output from the anomaly detection module and generates reports

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and notifications indicating the presence or absence of COPD-related anomalies. This module provides healthcare providers with actionable insights for patient management, such as recommendations for further diagnostic tests or changes in treatment plans. The module is also responsible for storing the detection results in the blockchain ledger, ensuring a secure and transparent record of the diagnosis.

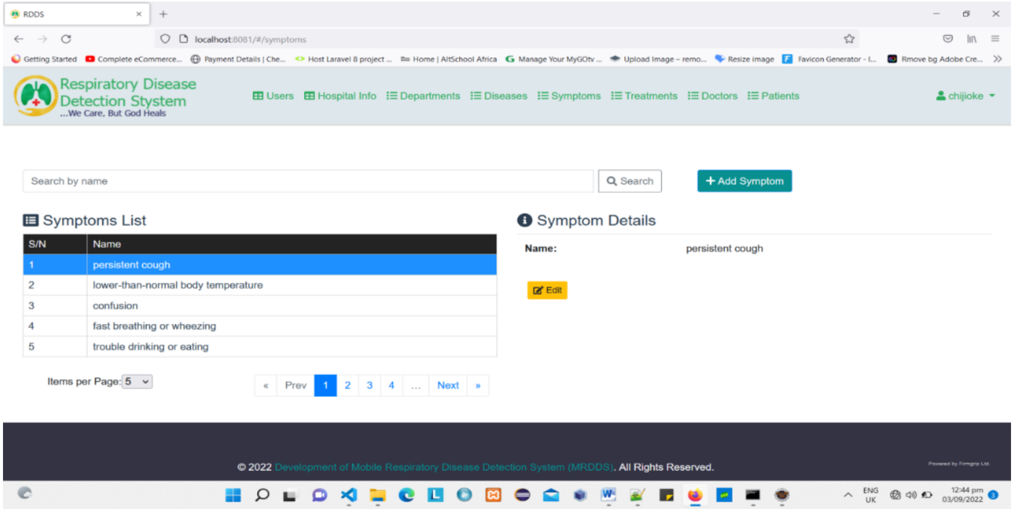

Figure 4: screen shot of the symptoms result of the patient.

IV. Conclusion

In conclusion, the proposed anomaly-based COPD detection system using machine learning demonstrated high accuracy and sensitivity in detecting COPD-related disease, with strong correlation with other measures of COPD severity. This framework offers a promising solution for early detection and monitoring of COPD, with the potential to improve patient outcomes and reduce healthcare costs. Further research is needed to validate the system in larger and more diverse populations, and to explore opportunities for real-world implementation in clinical settings.

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