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ARTIFICIAL INTELLIGENCE AND INTERNET OF THINGS ENABLED DISEASE DIAGNOSIS MODEL FOR SMART HEALTHCARE SYSTEM

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Abstract - Many diseases affect the elderly, including heart disease, high blood pressure, and diabetes. The medical infrastructure in Indian communities is deplorable. When one of the villagers becomes sick, the whole village suffers. A smart health care system is intended to monitor people's health condition from their homes. It relieves burden on physicians and hospitals while also saving the lives of many elderly individuals. Human body sensors include heart rate sensors, blood pressure sensors, blood sugar sensors, and temperature sensors. The sensors are linked to a medical app. The software is divided into two areas for users and physicians. Patients must first sign up for this app. The sensors detect and save patients' routine health details in the app's database. The data is analyzed by the system. If any data is determined to be incorrect, it is automatically sent to the closest hospital via GPS tracker, where action is taken immediately.

***Key Words*: IOT, Smart-Health**

INTRODUCTION

India's population is growing by the day. According to a recent report, India's population grows by over 15% per decade. As a result, the number of patients is expanding at the same pace. It will put strain on physicians and hospitals. If patients can be watched from home, the demand on physicians and hospitals would be minimized, and the government will save money. There are no effective treatment facilities in India's rural regions. There are certain areas in India where there is not a single doctor. When a patient's condition is critical, they confront a major challenge. To address these issues, We shall talk about a smart health care system in this article. The smart health care system is built using IOT.IOT stands for Internet of Things, which refers to internet-connected devices. We can control any material from anywhere with this IOT technology. Some sensors are attached to the human body and collect data.A health care app is using the data. All of the data is uploaded to the app's cloud database, which determines if the patients' condition is severe or not. If the patients' condition is determined to be critical, the data is instantly forwarded to the physicians, who take prompt action.

SYSTEM ANALYSIS:

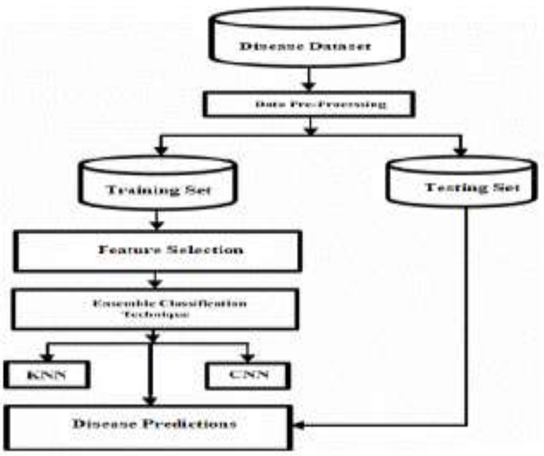
Existing System:

Chronic illness prediction is critical in healthcare informatics. It is critical to detect chronic diseases at an early stage. In the realm of healthcare communities, precise analysis and prediction play a critical role in determining the risk of sickness in the patient. However, when the data quality is limited and the medical data is in bad condition, the accuracy analysis is lowered, resulting in less prediction accuracy. We are looking for machine learning algorithms that can accurately forecast chronic illness. For organized and unstructured data, we suggest using a convolution neural network approach.

System Suggestions

With the advancement of machine learning technology, more attention has been paid to disease prediction from the perspective of big data analysis; various studies have been conducted by automatically selecting the characteristics from a large number of data to improve the accuracy of risk classification [1], [2], rather than the previously selected characteristics. The majority of previous research focused on structured data. Using a convolutional neural network (CNN) to extract text features automatically from unstructured data has previously gotten a lot of attention and produced outstanding results [3], [7]. However, none of CNN's past work has dealt with medical text data. Furthermore, illness severity varies among locations, owing mostly to differences in environment and lifestyle. The following issues remain in risk categorization based on big data analysis: What should be done about the missing data? and how should the primary chronic illnesses in a given area, as well as the key disease features in that region, be determined? How might big data analysis and machine learning technologies be utilized to forecast illness and improve models? As a solution, we use structured and unstructured data from the healthcare area to forecast and analyze illness risk. We present a CNN-based multimodal disease risk prediction (CNN-MDRP) method for structured and unstructured data. The disease risk model is created by combining structured and unstructured variables. Through the trial, we may infer that CNN-MDPR outperforms other available approaches.

ARCHITECTURE



MODULES:

Pharmacy The Medical data that has been preprocessed is loaded into iForest, a tree-based outlier prediction approach with linear time complexity and maximum accuracy. It can handle high-dimensional and massive amounts of data. Because the anomalies are 'mild and variable,' it is very susceptible to isolation. The records in a data-based random tree are cropped until isolation is completed. Random division produces outlier short-length records with identifiable values. It is advisable to split sooner [18] in this case. The iForest is made up of iTrees (Isolation Trees). Every iTree is considered a binary tree. The following are the stages involved in the execution process.

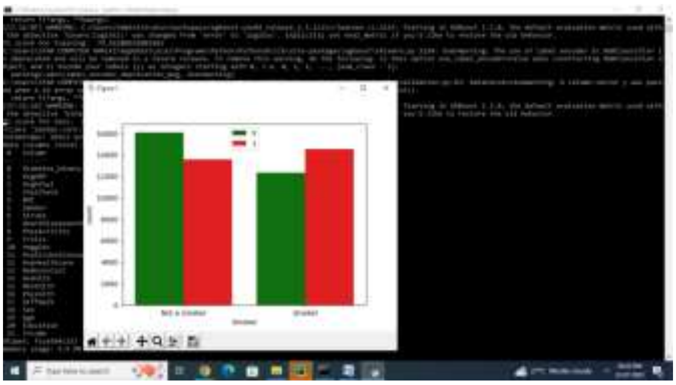
i. Take a few sample points from the training data and put them in the root node of a tree.

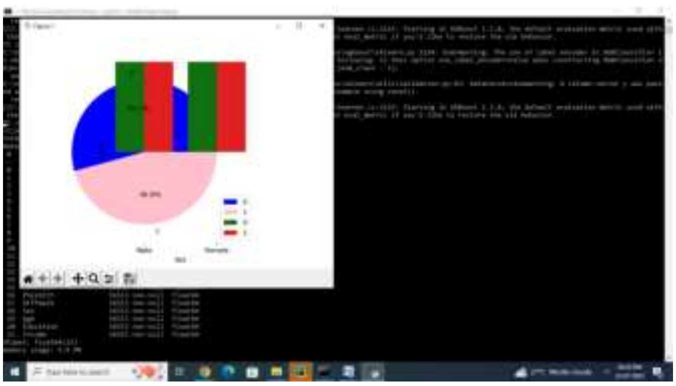
ii. Select an attribute and generate a cutting point 'p' using recent node data. Simultaneously, a cutting point is generated using the highest and lowest values of specific parameters in recent node data.

iii. A hyperplane is mimicked starting from the cutting point. While the data space of the recent node is divided into two subspaces, data that is less than 'p' in certain attributes and is put on the left child and data that is more than 'p' and is placed on the right child of the current node.

When the iTrees are completed, the iForest training is completed. The testing data is then approximated using the created iForest. When testing records, a traversal of all iTrees is taken into account, and the height of each record is computed. The average height of a record from each tree is then computed. When the average height is less than the imposed criterion, the record is considered an anomaly.

Results and Analysis:





Conclusion:

In this study, we examined the problem of drug traceability within pharmaceutical supply chains and emphasized its relevance, notably in the prevention of counterfeit pharmaceuticals. We developed and tested a blockchain-based pharmaceutical supply chain system for decentralized medication tracking and tracing. Our proposed solution, in particular, employs smart contracts on the Ethereum block chain to provide automatic event recording that is available to all stakeholders. This allows for tamper-proof logging of supply chain events.

In terms of the amount of gas required to carry out the different processes triggered by the smart contract, we have shown that our proposed technique is cost-effective. Furthermore, the results of the security analysis show that our proposed solution protects against malicious attempts to compromise the integrity, availability, and nonrepudiation of transaction data, all of which are critical in a complex multi-party setting like the pharmaceutical supply chain.
We want to expand the proposed system as part of our continuous efforts to enhance the efficiency of pharmaceutical supply chains in order to achieve end-to-end transparency and verifiability of medication usage.

ACKNOWLEDGEMENT

The heading should be viewed as a third-level heading and not given a number.

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