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Advanced Machine Learning model for Health Monitoring in IoT System

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Abstract: ***Health issues are also concealed by a lack of health precautions on a daily basis. These issues frequently constitute a serious threat to public safety, which is frequently overlooked until it is too late. As a result, we have developed a set of principles to address and, to some extent, solve the issues outlined above. We continuously monitor the vital organs in our system; communicate data to cloud-based doctors, and alert patients to potential dangers. We designed an IoT system that connects several sensors to a microcomputer and sends collected data to a cloud server for Modified Stochastic Gradient Descent(SGD) Algorithm with a combination of deep learning. If the doctor suspects a health problem, he or she may issue a warning via our device after the examination is completed.*** **Our proposed approach work** ***Health Monitoring in IoT System***
Keywords: machine Learning, Health Monitoring, IoT System, Deep Learning.

I. INTRODUCTION

With a better awareness of health and life and the advancement of medical technology, health has become an important issue of conversation today. There is plenty of time in ordinary life to walk around for the sake of health[1]. Some anomalies, such as heart disease and strokes, occur while walking, and because health difficulties, such as strokes, impair the capacity to move [2]. Stroke is becoming a more lethal disease[4], especially among persons over the age of sixty. There are numerous health issues that might arise as a result of a stroke. A stroke of sudden brain cell death[5] owing to lack of oxygen is caused by a blockage of brain flow or a blockage of blood arteries. Stroke symptoms include weakness in the arm or leg, or both, as well as balance loss, sore headaches, sluggish dizziness, coordination issues, eye trouble, speech problems, and facial muscle weakness[6]. One of the most prevalent are post-stroke disorders[7]. People who have had a stroke have lost consciousness and are unable to contact emergency or medical services. Without quick detection and treatment of a stroke, complications can be easily prevented and recovered[10]. A walking person's foot pressure is usually measured. In most situations, the accelerometer, gyro sensor, insole pressure sensor, pedometer, and GPS are used to gather the Gait parameter [11]. (Global Positioning System) The number of steps, the time of each step, the length of each step, the credence, the GRP (Ground Response Force), speed, and other critical parameters are all set. Cloud-based, integrative, security, and health services are crucial to the Internet of Things' (IoT) expansion of linked people. Several researchers are working on IoT health monitoring systems for a variety of reasons. One of the most common applications for wearable activity monitoring is gait tracking. Gait analysis is also employed in sports and medicine. The goal of this study was to illustrate how machine learning algorithms such as support vector and deep learning may be used to quickly classify patterns of stroke patience and older adult gateways. We have proposed a mechanism to track the occurrence of strokes in real time, particularly for the elderly.

II. RELATED WORK

This section covers a number of research projects relating to IoT applications and patient support systems. Various market applications are available. The purpose of these works is to assist persons with health issues, such as the elderly and those suffering from heart failure, diabetes, high blood pressure, cancer, and so on.

F. Ahamed et al[1] The study addresses concerns regarding model reliability and offers adjustments to certain of the machine learning model standards revealed in recent research.

X. J. Cai, et al[2] The goal of this research is to create an intelligent IoT system that can manage, interpret, and store patient data using IMU sensors. The study's key contribution is the ability to discern between static and dynamic persons, as well as the ability to save these assessments throughout time.

A. Das, et al[3] The construction of an IoT system that connects a number of sensors to a microsystem and sends the collected data to a cloud server for machine learning processing. If the doctor believes the patient's health is at risk as a result of the test, he or she may use our proposed device to send a risk report to the patient.

M. Ganesan et al[4] During the training phase, the classifier is trained using benchmark data. Actual disease identification patient data is used for disease detection throughout the testing phase. To experiment, a test data set with multiple classifiers is being used, including J48, LR, multi-layer perceptions, and vector support machines (SVM).

I. Azimi, et al[5]investigate if a classification model based on Convolutional Networks can be implemented in this architecture in this paper (CNN). Taking advantage of the HiCH and CNN properties, this offers exceptional availability and accuracy. offer real-time health surveillance using ECG classifications in a case study and analyse system performance in terms of response time and accuracy.

Rajawat A.S., et al[6] Take a look at our work, which depicts a cyber-attack and cyber-threat scenario for a concealed cyber world. We used device assaults to show how a CIA-based vulnerability analysis system can detect such attacks. In order to have a rational picture of the success of technologies, we measured performance using representative measurements.

III. PROPOSED METHODOLOGY

This research paper aims to propose a machine learning technique for analyzing the health data and is to employ a sensor to monitor patients from wearable devices using a sensor. Surveillance System Based on IoT Machine Lessons: The patient data was captured and sent to the hospital database using an IoT module. The proposed machine learning algorithm is used to classify the anomalous data from the gathered data. When data is entered into the database, it is checked to see if the information collected matches the patient's previous medical history. If it looks to be a problem, every data acquired from each patient's wearable sensor must be classed as data. The patient is notified after the data is more precisely categorised using the scheduled fast-recurring neural network. The architecture is depicted The model uses multivariate analysis in input and output parameters to classify these components in order to extract the proper aspects from homogenous medical conditions. To work on a usage data set . Data sets were separated into input and output parameters after being preprocessed for the extraction of prospective health and lifestyle parameter characteristics. Obesity, diabetes, and high blood pressure are the output parameters, whereas chronic disease-related components are discovered and displayed as input parameters. The patient's health and lifestyle are inputs, while the patient's status is the output. As the number of inputs to the model grows, the neural network's complexity grows. Dimensionality reduction techniques should be employed for successful analysis of linear and non-linear data. Two of the most significant devices for this are analytics and factor analyses of important elements. The massive data collection minimises the obtained data set's high dimensions.

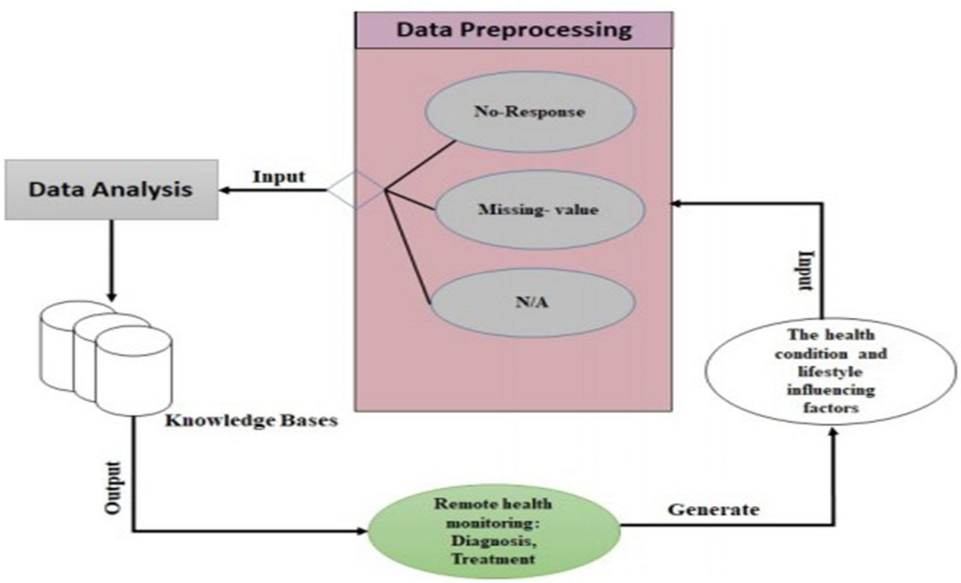

Figure 1:Data Pre-processing architecture for EHR data.

The proposed PFRNN's recurrent structure and its accompanying computational diagram are depicted for both the training and test phases. The x(t) R input is used to represent each step, with the dimensions of the vector Drera representing the number of unused outputs in the input function and the usingsoft max representing the number of hidden units at the kth layer. The input vector H(t) is the same as the input x(t) (k). (t)(t) H(t)(t) H(t)(t) H (k).

To produce the desired ybb output, O(t) is updated. the weight matrix U(e1 toD) parameters define x(t) connections between the Input and Hidden Layers; connections k and K+1 between hidden and hidden layers in the weight matrixV(k)[ek+1 and the weight matrixV(k)(sek) where k = l is parameterized; and connections k and K+1 between hidden and hidden layers in the weight matrixV(k)(sek) where k = l is It's worth mentioning that ek (1 = k/l) may dynamically adjust the flow of streaming data during training based on distributed changes in the input data. In the Support vector machine, hidden and output strata are also represented with pointed arrows, and the activation of the hyperplane is implicitly maintained within the hidden strata. Furthermore, no weight matrix is retained outside a repeated link between the hidden and output layers. As a result, the number of network parameters is drastically reduced, especially for deep networks. In actuality, it's beneficial to employ the hidden-output connection to accurately learn from prior timestamps' inputs and to improve parallels during exercises.

A. Support Vector Machine (SVM)

SVM is a very good ML algorithm compared to other machine learning techniques specially for solving classification and regression problems. It constructs optimal hyperplanes on the training data, by forming support vectors. Using these SVs and class labels, a dataset is formed and then this dataset is fed to classifiers and validated against the test set. It further classifies new instances based on this hyperplane which separates the classes in high-dimension space . SMO-Specific Efficient Optimization algorithm classifier is used . The below figure describes classification using a support vector. The data points in the circles are support vectors, shown in the below figure. Support Vector Machines classify data by building a hyperplane and are efficient in classifying huge data too and yield good results compared to the rest . The below *figure 1* shows classification in SVM.

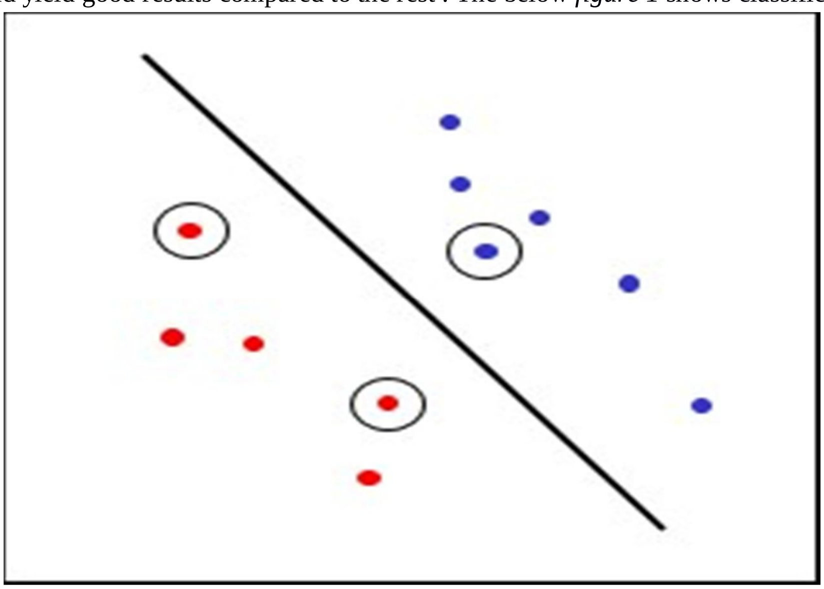

Figure 1: Classification in Support Vector Machine

Stochastic Gradient Descent Algorithm

SGD (Stochastic Gradient Descent) is a type of machine learning technique that is quite effective. Under the linear (SVM) and logistic regression convex loss functions, this is an effective technique to discriminatory learning of linear categories.

SGD is used to solve key learning challenges in text and other natural language processing applications.

It can scale issues with more than 105 training examples and more than 105 attributes well.

The following are the advantages of the Stochastic Gradient descent:

These are highly effective algorithms.

These algorithms are simple to implement.

However, the stochastic gradient descent (SGD) has the following drawbacks:

The SGD algorithm requires a number of regularisation hyperparameters and iterations.

It's also extremely sensitive to feature scaling, which is one of the most crucial data processing phases.

Algorithm 1 Applied the classification approach for determine the Correlated Factors with based on the concept of Pearson Correlation Coefficient Value

1) *Input:* select the health data set, Choose the value of thresholds
2) *Output:* Health results , positive , negative

a) Step 1 Number of input parameter
b) Step 2 if (novel efficient operation O in health data set) then
c) Step 3 Do (item E in o) do
d) Step 4 PCF = Pearson Correlation Coefficient (e);
e) Step 5 if (PCF ≥ Threshold) then
f) Step 6 Request Modified -class();
g) Step 7 return;
h) Step 11 Modified the class (input:factor e);
i) Step 12 PCF = grow Pearson Correlation Coefficient (e);
j) Step 13 if (PCF≥ 0) then
k) Step 14 Enhance e to PPPs;
l) Step 15 end
m) Step 16 else if (PCF≤ 0) then
n) Step 17 Enhance e to NPPs;
o) Step 20 Enhance e to NULL − class;

IV. RESULTS ANALYSIS

To perform the experiment using anaconda tool with python programming. Our system configuration is 16GB RAM and 1TB hard drive with 2.35GHZ i5 processor. The ROC and Gini coefficient are the most effective tools for evaluating categorization accuracy. In table 1, the AUC (curved area) and GINI coefficients represent the precision of several Machine Learn algorithms. Item 1 of the table The SVM model (AUC: 0.92, Gini: 0.82), LSVM model result (AUC: 0.93; Gini: 0.86), and stochastic gradient descent model outcome (AUC: 0.95) are all machine learning models that distinguish patient gait patterns and healthy patients.

Table 1: Health data classification using machine learning

Machine learning Model	Training		Testing		Validation	
	AUC	GINI	AUC	GINI	AUC	GINI
SVM	0.92	0.82	0.90	0.81	0.90	0.81
LSVM	0.93	0.86	0.91	0.85	0.91	0.85
stochastic gradient descent	0.95	0.93	0.91	0.90	0.91	0.90
Proposed algorithm	0.99	0.95	0.97	0.94	0.97	0.94

During data testing and validation, classification algorithms display similar trends as during the training phase. Model SVM has the lowest LSVM pattern categorization (AUC: 0.90, Gini: 0.81). (AUC: 0.93and Gini: 0.85).

The model is of the utmost accuracy. In the final validation phase, the model has the best precision (AUC: 0.90, Gini: 0.81) and the lowest precision (AUC: 0.91, Gini: 0.85). For various classification results, the ROC curve (or performance curve) is displayed . The Proposed algorithm algorithm helps patients and normal patterns (98 percent). SVM, LSVM, and stochastic gradient descent Continuous Area have values of 0.95, 0.93, 0.91, and 0.906, respectively. The SVM algorithm reveals the patient with the poorest performance and the most normal stroke characteristics (88 percent). The hemiplegic step differs from the usual gait due to sensory abnormalities . The outcome, including the altered gait pattern and normal, healthy gear, as well as the identified outcome, is predicted. To help susceptible stroke patients, effective IoT-guided monitoring and cloud-based machine learning of impaired and normal gait is required.

V. CONCLUSION AND FUTURE WORK

The usage of a health monitoring system is proposed in this study. All sensor data, data flows, system architecture, and ML model stroke prediction results are displayed. Additional bio signals, such as EEG, respiration, ECG, and sleep, must be added in the stroke monitoring system in order to prevent strokes in everyday situations, such as driving, sleeping, and working.in future we will try to implement in real time environment with different algorithms.

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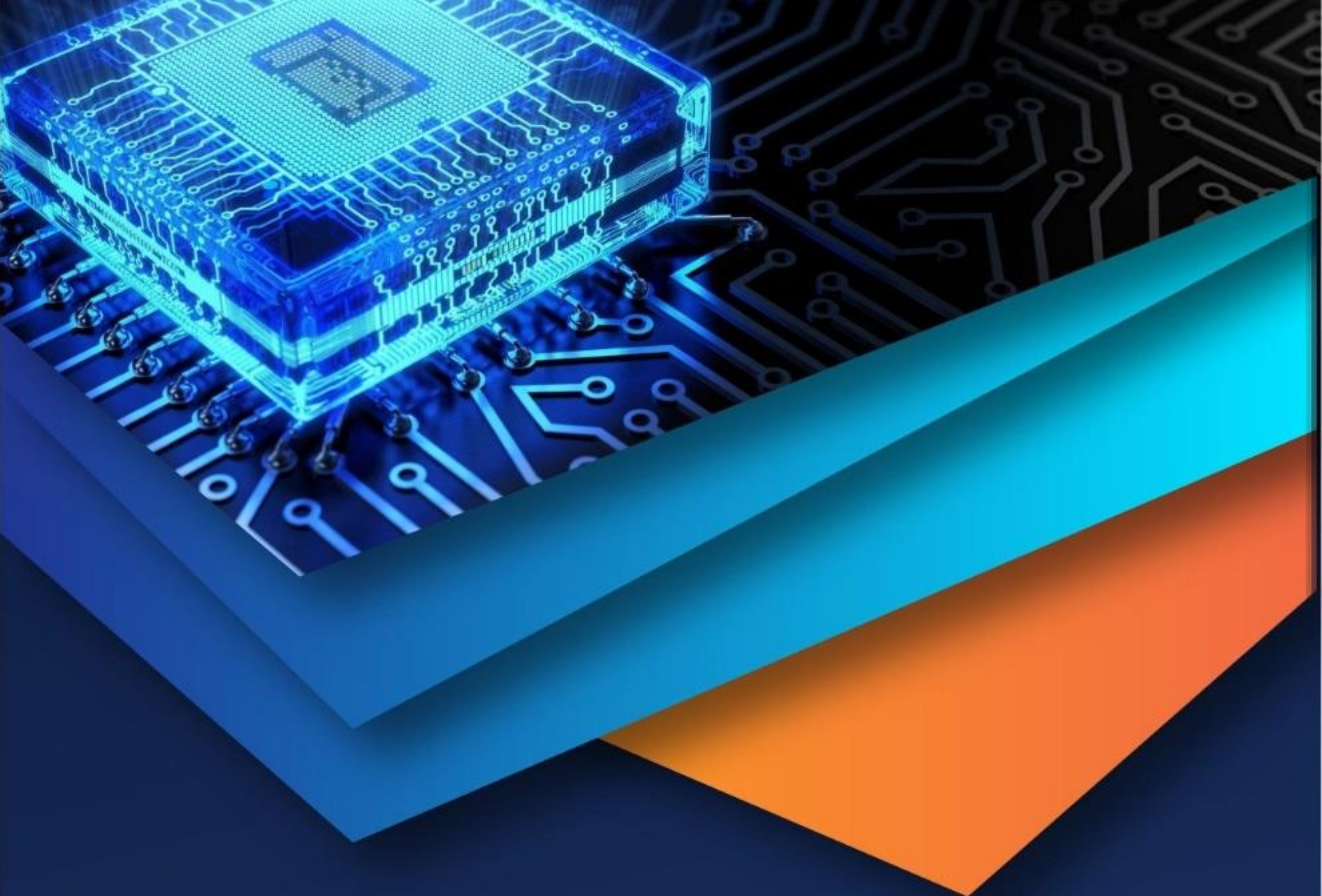

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