Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 4, April : 2023

PARALYSIS PATIENT HEALTH CARE MONITORING SYSTEM USING MACHINE LEARNING

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ABSTRACT:

Paralysis is the loss of muscle activity in a specific area of the body due to a disruption in the signaling process between the brain and muscles. IoT-based health monitoring can be an effective solution to the challenge of constantly monitoring patients in today's fast-paced society. However, like traditional monitoring methods, there are issues to consider, such as cost and patient-connected sensors. To improve the non-invasive monitoring system, machine learning methods can be used. In this project, a dataset is used on paralysis to develop a machine learning approach that involved KNN, label encoding and decision trees for data preprocessing and categorization. The proposed method can quickly assess a patient's health status, using a decision tree to predict the likelihood of paralysis and KNN to suggest appropriate exercises for patients with difficulties. Additionally, label encoding can transform labels into a numerical format that machines can read.

KEYWORDS: Decision Tree, KNN, Label encoding, Paralysis dataset, Patient health condition.

I. INTRODUCTION

Hospitals and organizations often treat patients with paralysis, a condition where an individual may have lost control over a part or all of their body due to damage to the brain's motor control centers. As a result, they may face difficulties communicating their needs effectively, whether through speech or sign language. The course of treatment and prognosis for the condition will depend on its underlying cause and the specific symptoms experienced by the patient. Fortunately, technological advancements and therapeutic techniques offer hope for maintaining patients' freedom and quality of life despite the challenges posed by paralysis.

Since paralysis involves a loss of movement in a specific body part, it is typically simple to identify, whether it's a small or large area. Sometimes, a tingling or numb sensation may be felt before complete paralysis sets in. Due to issues with the nervous system, the muscles in the affected area become difficult to control or entirely immobile, resulting in paralysis. Healthy nerves send signals to the muscles, prompting them to contract. With paralysis, this communication process is disrupted, leading to the inability to move certain parts of the body. Paralysis can also cause additional issues depending on its location, such as difficulty with breathing, blood flow, speech, eating, or controlling the urge to use the restroom.

II. RELATED WORK

In their paper published in the International Journal of Advanced Trends in Computer Science and Engineering, Zaheer Ahmed Wassan et al. [1] presented an a paralyzed patient's IoT-based smart home system uses an eye blink sensor.This sensor detects eye blinks and produces a voltage output when the eye is closed. To assist people with paralysis in controlling home appliances like air conditioning, fans, and lights. The TCRT 5000 eye blink sensor, Arduino-compatible micro-controllers, RF LINK pair modules, and Bluetooth technology were all used by the authors to build their system.

Amogh B et al. [2] introduced a gesture-based monitoring system for partially paralyzed patients in the International Journal of Engineering, Applied Sciences, and Technology. The project's methodology involves using a gyroscope to detect even the slightest body movements of a partially paralyzed individual. A gyroscope operates on the principle of conservation of angular momentum, where a rotor or spinning wheel is mounted on a pivot. Once the rotor is spun, the gyroscope will maintain its orientation. The authors utilized this technology to develop their monitoring system for paralyzed patients in 2022.

The researchers M. Kate et al. [3] proposed a monitoring system for paralysis patients that include multiple health sensors such as a skin galvanic response sensor, a heart pulse sensor, and a body temperature sensor. For the purpose of gathering and sending patient data to a cloud server, this sensor is linked to an Arduino UNO and a Raspberry Pi.The system also utilizes a digital MEMS accelerometer, which is compact and operates in a closed an effective bias-stabilized loop and repeatability of the scale factor. The accelerometer measures the x and y axes to capture the patient's acceleration data. The proposed system was published in the International Journal of Advanced Research in Science, Communication, and Technology in 2022.

Prajakta A. and colleagues [4] proposed an IoT-based system to improve the healthcare of paralyzed patients. The system is comprised of three modules: patient data acquisition and device control, the doctor's panel, and the patient panel. The Patient Data Acquisition and Device Control module serves as the primary component and is responsible for collecting sensor data and feeding it to an IoT-enabled microcontroller, which then sends the data to a web application that can be accessed by both the doctor and the patient. The microcontroller is equipped with a Wi-Fi chipset to establish connectivity with the web server via the patient's Wi-Fi network. This study was published in the International Journal of Engineering Applied Sciences and Technology in 2021.

Vidya Sarode et al [5] developed an automated paralysis patient health care system which includes a handicapped wheelchair. The wheelchair functions based on acceleration and incorporate one acceleration sensor for two axes. The sensor continuously sends an analog output that varies with the acceleration applied. The microcontroller is responsible for monitoring the sensor output and sending an SMS to the pre-defined number when necessary. The LCD display shows the output of the motion of the hand. This project was published in the International Research Journal of Engineering and Technology in 2021.

Table 1 Existing System Analysis

S.No	Author	Methodology	Merits	Demerits	Future Scope
1	Zaheer Ahmed Wassan	RF Link Pair modules, Bluetooth, an Ardunio compatible microcontroller, and TCRT 5000 as the eye blink sensor.	Over 70% accuracy is currently being provided by the system.	If the light has a variety of brightness levels and a negligible flicker rate, the user may find it challenging to blink more frequently.	In order to achieve hardware dependability and compatibility, we must address.
2	Amogh B	It is all about the sensing the slightest body moment of a partially paralyzed patient using a gyroscope	The movement of the hand will be tracked by the Gesture based watch. The Alarm will be given to the guardian on the phone	The device can be developed as a body vital measuring device and not just a Monitoring system.	By using machine learning like algorithm s, the device can be developed
3	M.Kate	On the video frames that were captured, the haar cascade algorithm is used to detect faces.	The eyes form a rectangular box, which allows us to focus on their movement with ease.	This analysis can be improved in the system because it is not effective in the dark.	Things that are audio and message-based in the study can be automated.
4	Prajakta	It collects the sensor's data and feeds to the IoT enabled microcontroller which acts as a brain of this System.	It gathers sensor data and transmits it to the system's brain, an IoT-capable microcontroller.	It is not Applicable for every paralysis patient. It should be designed according to the patient condition	In future more parameters can be added

5	Vidya Sarode	They used handicap wheelchair which basically works on the principle of acceleration	The program is developed to count those blinks where the strength value is 50 to 51 as a blink counter	A provision to send SMS alerts can be added for guardians in case of wheelchair malfunctions due to Mechanical problems or accidents.	Some extra Features can be added in the future to improve the functionality.

III. PROPOSED SYSTEM

The model proposed in this study incorporates machine learning algorithms to effectively build a system that can process a paralysis dataset as input. To improve the accuracy and reliability of the system, implemented a data preprocessing step that involved handling missing values using the panda's package. If any missing values were found, they were replaced by zero or NaN values. To encode the labels for the input data and columns into numeric values, we used the functions isnull() and fillna() for label encoding. Data splitting: In this step, the preprocessed data is split into train data and test data. Machine learning algorithms such as KNN and decision tree were utilized for categorization and preprocessing. By eliminating noisy data and operating with precision, the system makes it easier to identify the health status of patients.

Decision Tree: A supervised learning technique frequently employed for classification issues is the decision tree, although they can also be used for regression problems. They are organized like a tree, with internal nodes for various dataset features, branches for the decision-making process, and leaf nodes for the classification outcome. Decision tree is often used for classification tasks due to their tree-based structure.

KNN: A fundamental machine learning algorithm that makes use of the supervised learning strategy is K-Nearest Neighbor. The K-NN algorithm classifies new instances based on how closely they resemble existing categories, working under the assumption that new cases and existing cases are comparable. The category that most resembles the other categories is chosen by this algorithm.

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ISSN: 0970-2555
Volume : 52, Issue 4, April : 2023

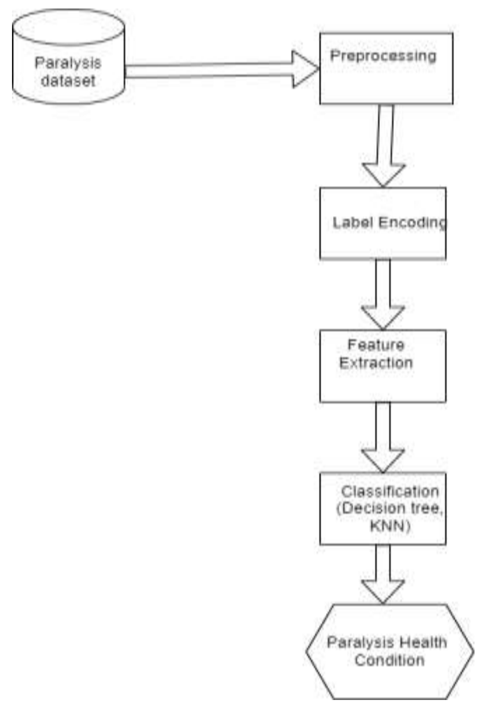

Fig 1: Proposed Model for Paralysis patient health condition

DATA SELECTION:

Step 1: The input data utilized in this study was gathered from various sources, such as dataset repositories like UCI, GitHub and Kaggle, among others. For analysis, utilized the stroke dataset.

Step 2: The dataset used in this study contains information about the patients, including their ID, gender, age, hypertension status, heart disease status, marital status, work type, residence type, average glucose level, BMI, smoking status, and whether or not they had a stroke.

Step 3: panda’s package is used to read the input dataset, which was in CSV format.

DATA PREPROCESSING:

Step 1: Data pre-processing involves eliminating any irrelevant data from the dataset. This step may also involve transforming the dataset into a format that is more suitable for machine learning through the use of data transformation operations.

Step 2: Cleaning the dataset of any irrelevant or corrupted data that might negatively affect its accuracy is another aspect of data pre-processing. The dataset's effectiveness for machine learning is improved by this cleaning procedure.

Step 3: Missing Data Removal: Any null values, such as missing values or NaN values, were changed during this process to a value of 0. The data was also cleaned of any anomalies and duplicate values were eliminated.

Step 4: Encoding Categorical Data: Variables with a limited number of label values are referred to as categorical data. Numeral input and output variables are necessary for the majority of machine learning algorithms, so it is necessary to encode categorical data into numerical values for use in these algorithms.

DATA SPLITTING:

Step 1: Machine learning depends heavily on data to facilitate learning. In addition to the training data, it is essential to have separate test data to evaluate the algorithm's performance and effectiveness.

Step 2: To evaluate model's performance, It divided the disease dataset into two portions - 80% for training and 20% for testing. This process, known as data splitting, involves partitioning available data into distinct subsets, typically for cross-validation purposes.

Step 3: Developing a predictive model involves splitting the data into two parts: one for model development and the other for model evaluation. This separation of data into training and testing sets is a crucial step in the evaluation of data mining models.

Step 4: When dividing a dataset into training and testing sets, the majority of the data is typically allocated to the training set, with a smaller portion reserved for testing purposes. This approach ensures that the model is trained on a large enough dataset to accurately capture patterns and trends, while also allowing for a thorough evaluation of the model's performance.

CLASSIFICATION:

Step 1: In the field of machine learning, classification refers to the task of predicting a class label for a given input data example. This type of predictive modeling problem deals with the prediction of discrete class labels. In contrast, regression involves predicting a continuous quantity, which sets it apart from classification.

Step 2: Classification is a supervised learning technique in machine learning that involves grouping a set of data into distinct classes or categories. To ensure accurate classification, it is necessary to first divide the data into separate training and testing sets. This partitioning of data enables the model to be trained on a portion of the data and tested on the remainder, ensuring that the model is not over fit to the training data.

Step 3: When splitting a dataset into training and testing sets, the majority of the data is allocated to the training set, while a smaller portion is reserved for testing. While the testing data is used to make predictions with the model, the training data is used to assess the model. This approach allows for the evaluation of the model's performance on data that it has not seen before, providing a measure of its generalization ability.

Step 4: Once the data has been split into training and testing sets, the next step is to apply a classification algorithm. In our study, we evaluated the effectiveness of several classification algorithms, including decision trees and KNN. These algorithms were used to build models that could accurately classify data into distinct categories.

PERFORMANCE ESTIMATION:

The overall precision of the model's predictions determines the classification method's final outcome. To assess the effectiveness of the approach, utilized several measures are included in this paper. These metrics were used to assess the proposed classification algorithm's performance and as certain how well it predicted the classes for the input data.

Accuracy

A classifier's accuracy is measured by how well it can predict the class label for a specific input data instance. It is typically expressed as the proportion of accurate predictions over all predictions. On the other hand, a predictor's accuracy refers to how well it can predict the value of the predicted attribute for fresh data instances. A classifier's accuracy is frequently determined using the following formula:

AC = (TP + TN) / (TP + TN + FP + FN)

Where TP, TN, FP, FN, and FP respectively stand for true positives, true negatives, false positives, and false negatives.

Precision

A performance metric called precision is used to assess how well a classifier detects true positives. By dividing the sum of true positives and false positives by the total number of true positives, it is calculated. The formula for accuracy is:

Precision = TP / (TP + FP)

Where FP stands for false positives and TP for true positives.

Recall

Recall is a performance metric that assesses a classifier's capacity to locate every successful instance in the input data. Recall and sensitivity are synonyms for binary classification. The amount is calculated by dividing the sum of true positives by the sum of true positives and false negatives. Calculating recall is done as follows:

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 4, April : 2023

Recall = TP / (TP + FN)

Where TP stands for true positives and FN for false negatives. Recall can be understood as the likelihood that a relevant example in the input data will be correctly identified by the classifier.

F1_Score

The F1-score is a widely used performance metric for classification models, as it provides a balanced measure of both precision and recall, even in cases where class imbalance is present. Its value ranges from 0 to 1, with higher values indicating better model performance, and it is calculated as the weighted average of the recall and precision scores for each class. The minimum and maximum F1 scores are 0 and 1, respectively.

F1-score = 2 * (precision * recall) / (precision + recall)

IV. RESULTS AND DISCUSSION

Dealing with missing values is an important step in enhancing the accuracy and efficiency of machine learning models. One way to identify missing values in a dataset is by using the isnull() function, which returns a boolean value indicating whether a value in a particular column is missing or not. By detecting and handling missing values appropriately, It can avoid introducing bias into the models and improve their overall performance.

```
----------------------------------------------------
Before Handling Missing values
----------------------------------------------------

id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

Fig 2: Before handling missing values in paralysis dataset

After identifying missing values in dataset using the isnull() function, To handle them appropriately and to avoid introducing bias into the models. One way to handle missing values is by using the fillna() function, which replaces the missing values in a particular column with a specified value, such as 0. By replacing missing values with appropriate values, It can ensure that models are able to utilize all available data, leading to better performance and more accurate predictions.

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ISSN: 0970-2555
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```
---------------------------------------------------
 After Handling Missing Values
---------------------------------------------------

id                   0
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

Fig 3: After Handling Missing values in paralysis dataset

Label encoding is a technique used to convert categorical labels into numerical values between 0 and 1 to assign appropriate numerical values to each categorical label. For instance, we designated the value 0 to represent "female" and the value 1 to represent "male" in our dataset. By performing label encoding, machine learning models are able to handle categorical data and make accurate predictions based on this data.

```
---------------------------------------------------
Before Label Encoding
---------------------------------------------------

0      Male
1    Female
2      Male
3    Female
4    Female
5      Male
6      Male
7    Female
8    Female
9    Female
Name: gender, dtype: object
```

Fig 4: Before Label encoding

The fit_transform() method is commonly used in machine learning to scale and transform the training data. This method applies both the fit() and transform() functions to the training data in a single step. During the fit() step, the scaling parameters are learned from the training data. Then, during the transform() step, the training data is transformed into a new format that is better suited for the machine learning model. By using fit_transform(), efficiently preprocess the training data and

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ISSN: 0970-2555
Volume : 52, Issue 4, April : 2023

prepare it for model training.

```
---------------------------------------------------
After Label Encoding
---------------------------------------------------

0    1
1    0
2    1
3    0
4    0
5    1
6    1
7    0
8    0
9    0
Name: gender, dtype: int32
```

Fig 5: After Label Encoding

It can be utilized various metrics, including accuracy, precision, recall, F1 score, and support to estimate performance.

```
---------------------------------------------------

Total no of data        : 5110
Total no of test data   : 1022
Total no of train data  : 4088

---------------------------------------------------
Machine Learning ----> Decision Tree
---------------------------------------------------

1. Accuracy = 92.17221135029354 %

2. Classification Report:

              precision    recall  f1-score   support

           0       0.96      0.96      0.96       968
           1       0.24      0.22      0.23        54

    accuracy                           0.92      1022
   macro avg       0.60      0.59      0.59      1022
```

Fig 6: Decision Tree

It's crucial to assess a machine learning model's performance using the right metrics. Metrics includes the number of standard metrics, support, recall, accuracy, precision, and F1 score. The effectiveness of the model's classification and prediction of the target variable based on the input data can be evaluated using these metrics. To determine the model's strengths and weaknesses and make the necessary corrections or improvements by examining the outcomes of these performance metrics.

```
------------------------------------------------
Machine Learning ----> K Nearest Neighbour
------------------------------------------------

1. Accuracy = 94.42270058708415 %

2. Classification Report:

              precision    recall  f1-score   support

           0       0.95      0.99      0.97       968
           1       0.29      0.04      0.07        54

    accuracy                           0.94      1022
   macro avg       0.62      0.52      0.52      1022
weighted avg       0.91      0.94      0.92      1022
```

Fig 7: K Nearest Neighbour

V. CONCLUSION AND FUTURE SCOPE

In this paper, the development of the system is involved to classify whether a patient is affected by paralysis or not, using different classification algorithms such as KNN and Decision Tree. These models effectively generate KNN with 94% and Decision tree 92%. Additionally, the experiments yielded performance metrics included accuracy, precision, recall, and f1-score. In future, it will hybridize the two different machine learning algorithms, combine the two different deep learning algorithms, or combine machine learning with deep learning algorithms.

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