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# Measuring Stroke Rehabilitation By Posture Detection Using Neural Networks

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***Abstract:*** More than 795 thousand people in the US experience a stroke, per year. Out of this, around 610 thousand are RST or new strokes. [2] Strokes are a leading factor of mortality for Americans with 140 thousand people dying annually. [3] Stroke incidence has increased drastically in the young population, with over 20% of those affected being under the age of 45. Hemiparesis, which occurs following a stroke, is a significant motor impairment that affects up to 65 percent of stroke sufferers because of a high rate of muscle frailty. [4] Muscle pain is a significant role in delayed recovery following stroke in victims, and it is also a common symptom reported in patients. This can result in a patient's range of physical activities being limited or even immobilized. Between 30% and 60% of stroke victims report having less physical range in the damaged body portion when performing daily activities. [5] The feasibility of a 4 by 4 excible sensor matrix which uses paper as a base is explored and a pressure sensor based on paper is developed. This helps reduce the cost and fabrication time. Additionally, the matrix's static and dynamic properties are discussed. Despite considerable variance in response between sensors due to the structural material qualities, the sensor may be efficiently used to continuously evaluate stroke rehabilitation patients' recovery. The matrix's performance is evaluated using a neural network that has been designed to recognize the location of a load using the values of individual sensors.

***Index Terms* -** Artificial Intelligence, Stroke, Recurrent Neural Network, Sensors

## I. INTRODUCTION

Strokes mostly occur in combination with other medical diagnoses. Current stroke rehabilitation evidence, however, is not focused on the comorbidities and therefore does not align with the experiences of the current population. The motivation behind this study is to decide the degree and nature of the ongoing randomized and controlled preliminary of stroke restoration with an emphasis on patients with multimorbidity. Stroke recovery is often incomplete, but rehabilitation training can help recovery outcomes by engaging endogenous neuroplasty. High doses of training are needed in pre-clinical models of stroke rehabilitation to recover the physical activity of the impacted appendages in animals. However, in human body the required training to help recouping rate is unknown. The lack of pragmatic and objective approaches to measuring the rehabilitation training doses adds to this ignorance. To develop a proper measurement approach, the primitives of activities are to be identified. Examples of primitives include running, jumping, and walking. In our review, forty-eight individuals with chronic stroke are chosen to perform a variety of stroke rehabilitation training activities. To capture the upper body movements the individuals, use inertial measurement units or IMUs. Human labellers are used to identify the primitive activities and to label and segment the IMU data. A recurrent neural network (RNN) is designed that outperforms existing techniques. To compute the separate embeddings of the various physical quantities of the sensor data an initial module is included in the proposed algorithm. The proposed technique swaps the batch normalization, which uses measurements processed from training data to perform normalization, with instance normalization, that uses measurements processed from test data. The result is increased robustness towards possible distributional shifts when encountering new patients.

A common side-effect of stroke is muscle weakening which often results in the reduction of the range of movement of the impacted body part. A wide scope of physical training is included in stroke rehabilitation which can help the patients re-establish and develop body fortitude, endurance, balance, and stability. A 4 by 4 excible pressure matrix is used to analyse and identify the movement of the body while performing the training exercises. The sensor can be used to measure the performance of a stroke rehabilitation patient and mark their progress. An AI based algorithm is presented to measure the positioning accuracy of stroke sufferers. Assessment shows that the proposed calculation has a mean blunder of 0.103 cm in recognizing load while numerical investigation gives a mean mistake of 0.704 cm. The pressure sensor can be used to calculate the mistake in the training exercise positioning and can also calculate the duration to complete the exercises.

## II. Literature Survey

The authors Muhammad Salman et al in their paper “Identifying Stroke Indicators Using Rough Sets”, sought to rank various EHR (Electronic Healthcare Records) records in the order of importance that can be used to detect a stroke. [6] A novel rough-set technique was devised which, unlike the conventional techniques, can be used on any dataset that comprises binary feature sets. The proposed algorithm was then evaluated using a public dataset of EHR records. The conclusions that were drawn from the evaluation are that hypertension, heart disease, average glucose level, and age were the most important attributes to help detect strokes in patients. The proposed algorithm was then benchmarked with popular feature-selection algorithms. The proposed technique obtained the best performance in ranking the importance of individual features to detect stroke.

Stroke rehabilitation patients frequently engage in compensatory behaviours without the supervision of a therapist, resulting in unsatisfactory recovery outcomes. Siqi Cai et al. studied the idea of real-time monitoring of compensation in stroke rehab patients in their paper "Real-Time Detection of Compensatory Patterns in Patients with Stroke to Reduce Compensation During Robotic Rehabilitation Therapy" [7]. This was accomplished using pressure distribution data and machine learning methods. Trunk compensation reduction was also investigated using a combination of online compensation detection and haptic input from a rehab robot. To classify the online compensatory patterns, an SVR classifier (Support vector machine) was trained. The training dataset consists of pressure distribution data from six stroke patients performing three distinct types of reaching movements. Stroke patients were assisted by a rehabilitation robot to lessen compensatory movements. The suggested algorithm's excellent classification accuracy demonstrated the viability of employing pressure distribution data to decrease compensatory movements in stroke patients. The proposed approach was combined with a rehabilitation assistive robot to help stroke sufferers with truck compensations.

Roger M. Sarmento et al. presented a systematic assessment of existing computational approaches for the detection, segmentation, and identification of strokes using medical images. [8] To increase the diagnosis process's accuracy and consistency of interpretation of such image data, CAD (Computer-Aided Diagnosis) systems have been developed using a variety of technologies, including digital image processing methods, and artificial intelligence. However, limited sensitivity, a reduction in false positives, algorithm optimization, and an increase in the identification and classification of varied shapes and sizes are some areas where the presented methodologies could be improved. The classification steps for various stroke types and subtypes, in particular, were cited as areas for improvement. Their research focuses mostly on examining the strategies used to construct CAD systems and validating their efficacy for stroke identification, segmentation, and categorization.

The authors Anis Fatema et al. examined the effects of stroke on recovering patients' motor controls and mobility in their work "A Low-Cost Pressure Sensor Matrix for Activity Monitoring in Stroke Patients Using Artificial Intelligence." [1] As muscle pain is a typical complication of stroke, the researchers created a 4 by 4 pressure sensor matrix to assess the performance and development of patients receiving post-stroke physiotherapy. A series of movement exercises using the pressure sensor matrix with the objective of estimating the force exerted and the movement inaccuracy.

## III. METHODOLOGY

### 3.1 Architecture Diagram

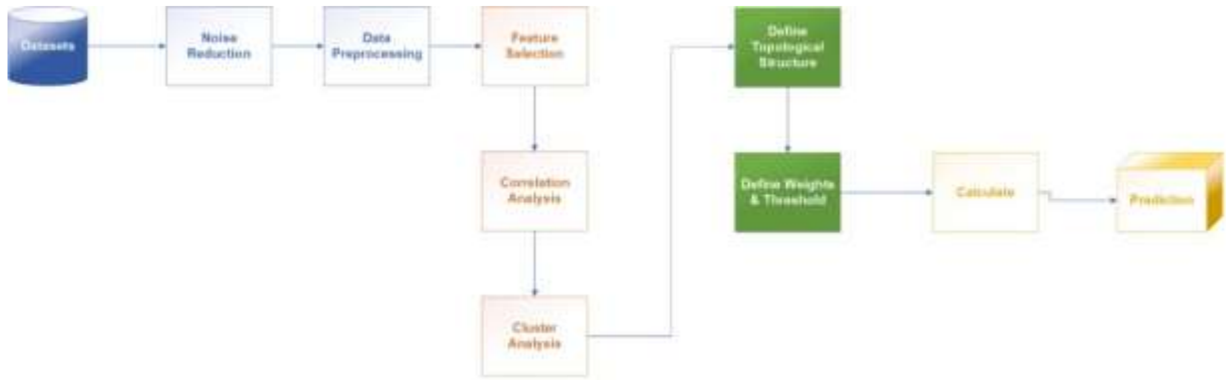



Figure 1 Architecture Diagram

### 3.2 Imputation Details

Imputation of data is the handling of missing values in our dataset. One method to deal with missing data is to delete the records that contain the missing values, but this could lead to losing out on valuable information. There are various types of imputation. [9] Categorical imputations relate to the missing categorical values in the dataset. The missing data, in this case, is replaced by the most commonly occurring record in the dataset. Numerical imputation deals with missing numeric values in the dataset, the values are generally filled with the mean of the corresponding value in other records. From the imputation data collected we have consolidated a dataset which is used as the value source for the prediction of the model. Before proceeding further, we clean the dataset from possible noise that could have entered it, through means of standardization, duplicate deletion, and elimination of null values.

### 3.3 Feature Extraction

Selection methods like Feature extraction can be utilized in isolation or in union with each other to increase efficiency of the working of the model. It can be used to work on the precision, visualization, and comprehension of the learned information. Elements can be delegated relevant, irrelevant, or excess. [10] A subset of the accessible information is chosen, in this process. The best subset to pick is unified with the most un-number of aspects that add to learning exactness. [11] Information gain evaluates the gain of each individual feature with respect to the target variable. The larger the information gain, the larger will be the contribution of the characteristics to the text. The characteristics with higher information gain are selected to be Features. Dimensionality reduction is a popular pre-processing method in data analysis, modeling, and visualization. This can be easily achieved using Feature Selection as we can only select the input characteristics that contain information relevant to solving the problem at hand. They can be further classified into Feature weighting methods and subset search methods. [12] This method has a low process expense and is faster. However, they are also not very reliable in classification when compared to wrapper methods and are more suited to high dimensional data sets. Hybrid techniques have been created which consolidate the benefits of filters as well as wrapper strategies. To weigh the features to extract patterns and perform exploratory data analysis, we map labels to the different activities performed by the test subjects, recorded in the dataset. From the label map, we can further analyze the activities performed by each subject and further understand the data to draw patterns from it through means of multivariate feature analysis.

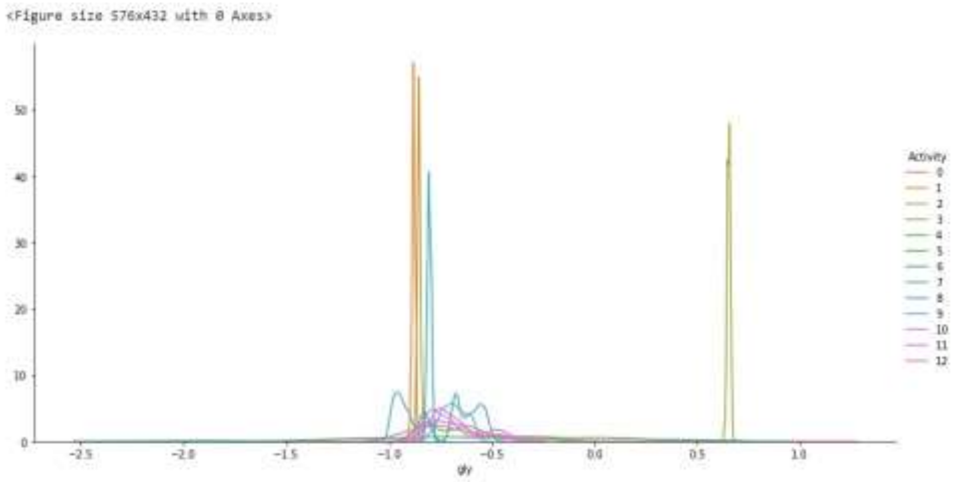
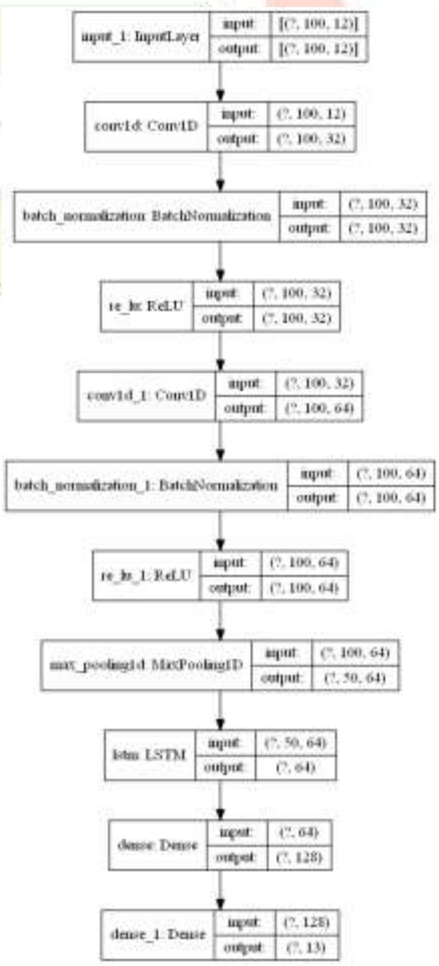



Figure 2 Frequency distribution of Activity for Y axis movement

**3. Prediction**

Neural Networks are a series of algorithms that aim to recognize underlying patterns in data in a way that mimics the human brain. It can be used for classification, prediction, and other such purposes. Higher the number of hidden layers and therefore a greater number of neurons and connections a neural network has, the more complex it is. What allows the neural network to learn complicated patterns that are hidden in the data is this complexity. In a neural network, changing the weight of anyone connection has a ripple impact on the wide range of various neurons and their initiations in the ensuing layers. A RNN (Recurrent Neural Network) is a kind of neural network that solves the problem of vanishing gradients as it incorporates the backpropagation algorithm. [13] Therefore, it is useful for complicated sequence problems that occur in ML (Machine Learning) and can even attain SOTA (state-of-the-art) results. The RNN has memory blocks that are connected through layers, instead of neurons. The memory blocks have components that enable them to store memory for latest sequences. The blocks contain gates that maintain the state and




output of the block. The gates use sigmoid activation units to act upon the input sequence to control if the block is triggered or not. [14] This enables the change of state of the block and any addition of information to the block to be conditional. Figure 3 shows the neural map of the network we have developed with a total of 50,797 parameters out of which 50,605 parameters are trainable. From this neural network we have achieved an accuracy of 95.4% during test scenarios as depicted by Figure 4.

Figure 3 Neural Network Map

Figure 4 Model Loss and Accuracy visualization

## IV. Results And Discussion

A 2D hexagonal binning graph is plotted from the acceleration data from the left ankle sensor and the acceleration data from the right lower arm sensor. The data from when the subject is standing still is represented in Figure 5 and the data from when the subject is climbing stairs is represented in Figure 6. By examining both the graphs, it is clear that the static activities like standing still are different and can be separated from dynamic activities like jumping and climbing stairs.

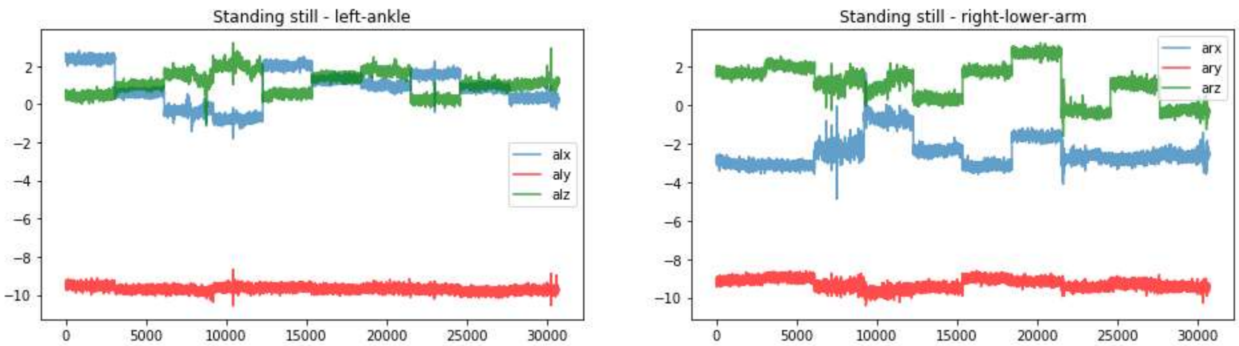
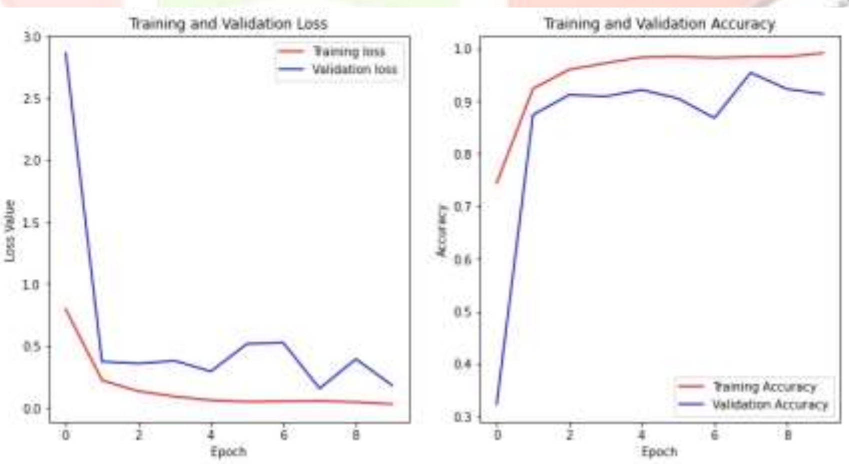



Figure 5 2D Line graph of data from the sensors while subject stands still



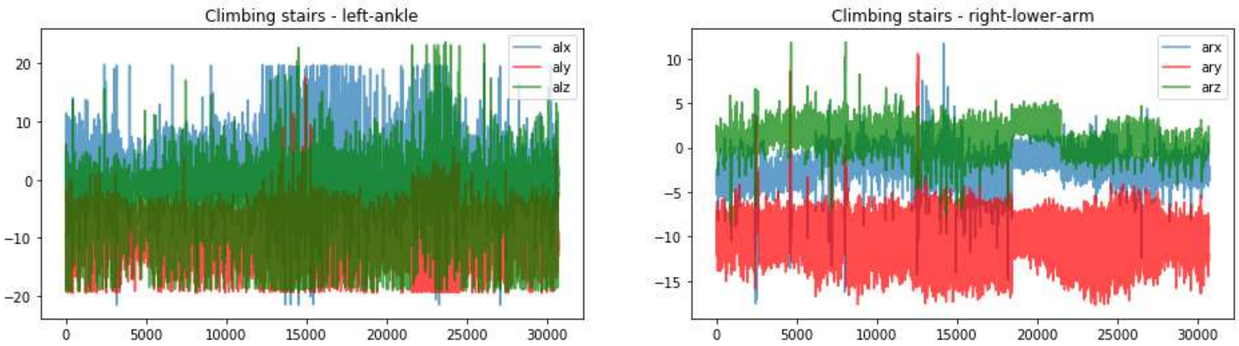




Figure 6 2D Line graph of data from the sensors while subject climbs stairs

After understanding the data, it is then possible to apply the data to our model. A confusion matrix is then plotted to evaluate the model. A confusion matrix provides a visual representation of the performance of classification algorithms. The actual and predicted values are plotted against each other such that there are four different combinations - False positive, True positive, False negative and True negative. From the matrix, it is clear that the data is predicted to a good accuracy as the centre diagonal is darker than the surrounding boxes.

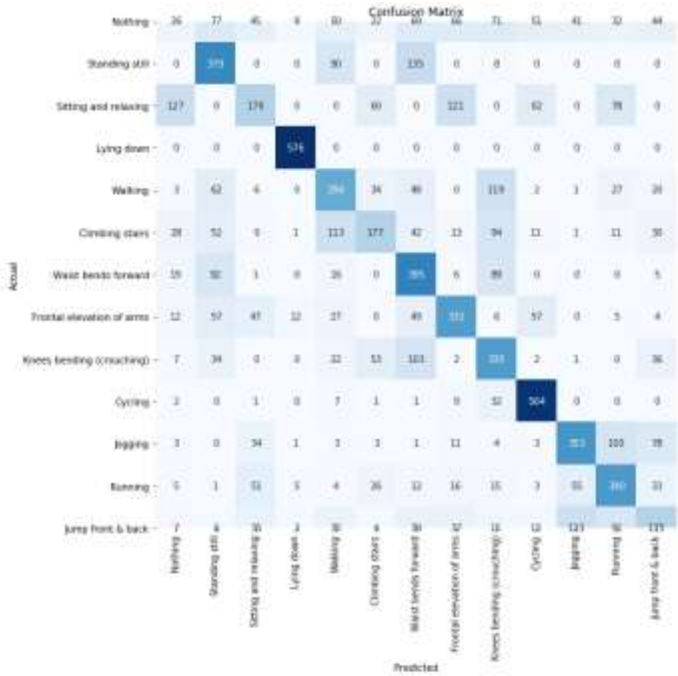



Figure 8 Confusion Matrix

To further evaluate the model, a classification report is generated. A classification report is a metric used for performance evaluation that displays the precision, recall, f1-score and support of the model. The following conclusions are drawn from the report –

- The accuracy of the model is 98% which indicates that the model performs well on our data. Support represents the number of actual observations of the specific class in the dataset.
- Precision gives the ratio of correctly predicted observations compared to the total predictions. We can see the general trend of precision for the various activities is close to 1, which is ideal.
- Recall is the ratio of correctly predicted observations to the total observations. From our results, it is seen that recall is generally higher than 0.8. This is good for this model.
- F1-score is a weighted average of precision and recall. This is generally considered to be a better measure than accuracy. A low F1 score shows poor precision and recall. From the classification report, it is seen that the average score is close to 1.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.99 | 0.99 | 89 |
| 1 | 0.98 | 1.00 | 0.99 | 122 |
| 2 | 0.99 | 1.00 | 1.00 | 123 |
| 3 | 1.00 | 0.99 | 1.00 | 123 |
| 4 | 1.00 | 1.00 | 1.00 | 120 |
| 5 | 0.98 | 0.96 | 0.97 | 85 |
| 6 | 0.88 | 0.99 | 0.93 | 105 |
| 7 | 0.99 | 0.99 | 0.99 | 112 |
| 8 | 0.97 | 0.86 | 0.91 | 117 |
| 9 | 1.00 | 1.00 | 1.00 | 120 |
| 10 | 0.99 | 1.00 | 0.99 | 89 |
| 11 | 1.00 | 0.98 | 0.99 | 53 |
| 12 | 1.00 | 1.00 | 1.00 | 26 |
| accuracy | | | 0.98 | 1284 |
| macro avg | 0.98 | 0.98 | 0.98 | 1284 |
| weighted avg | 0.98 | 0.98 | 0.98 | 1284 |

Figure 9 Classification Report

## V. CONCLUSION

A novel dataset was introduced that can be used by benchmarking algorithms to detect and classify upper-limb mobility compensatory movements during stroke rehabilitation exercises. The benchmarking algorithms can be used for providing real-time automated stroke rehabilitation coaching and can be merged with rehabilitation robots to assess and correct compensatory movements during training exercises in stroke victims. A baseline model was presented that is used to demonstrate the usefulness of the dataset. The angle of the trunk vector or the shoulder vector is compared to the compensatory movements to examine the results. The specificity and sensitivity of the classification were also shown.

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