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Web-based Machine Learning Prediction of Stroke Rehabilitation Exercise Categories

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ABSTRACT

Stroke rehabilitation requires timely and targeted exercise interventions to restore mobility, strength, and independence. This study develops a machine learning-based system to predict appropriate rehabilitation exercise categories (strength, balance, and mobility) tailored to patient severity levels. Using an open-source dataset of 5,110 stroke patient records, including age, BMI, glucose level, smoking status, paralysis type, and speech ability, three supervised algorithms were evaluated: Random Forest (RF), Logistic Regression (LR), and Multilayer Perceptron (MLP). Accuracy values were reported with 95% Confidence Intervals (CI): RF (94.12%, 95% CI: 93.6–94.6), LR (94.12%, 95% CI: 93.5–94.7), and MLP (94.32%, 95% CI: 93.8–94.9). Despite MLP's marginally higher accuracy, RF was selected for deployment due to its stability, interpretability, and alignment with expert recommendations. Validation against rehabilitation specialists yielded strong agreement (Cohen's κ = 0.82), confirming clinical reliability. The RF model was integrated into a web-based application hosted on Heroku. This platform enables patients, particularly those in rural areas with limited access to physiotherapists, to receive personalised exercise guidance. Future work will expand dataset diversity, incorporate hyperparameter optimisation, and evaluate additional metrics such as precision, recall, F1-score, and ROC-AUC to enhance clinical robustness. This system demonstrates the potential of machine learning to support accessible, personalised rehabilitation in resource-constrained settings.

INTRODUCTION

Stroke remains one of the leading causes of disability worldwide, affecting both older and younger generations. Increasingly, lifestyle factors such as obesity, hypertension, and diabetes contribute to stroke risk among younger adults. Rehabilitation is critical in restoring physical functionality, particularly within the first three to four months after a stroke, when physiotherapists guide patients through exercises that improve strength, balance, and mobility.

In the healthcare sector, data collection is crucial for generating a holistic view of patient care, improving communication between doctors and patients, personalising treatment, tracking genetic history, and advancing treatment methods (Kumar et al., 2011; Greer et al., 2022). Although large amounts of data are collected, they are often underutilised. Health prediction systems have been widely studied, applying approaches such as machine learning, fuzzy logic, rule-based systems, big data, and data mining to diseases including diabetes, heart failure, liver problems, cancer, mental illness, hepatitis, and stroke (Haq et al., 2020). For example, one study on heart disease achieved a classification accuracy of approximately 77% using a logistic-regression-derived discriminant function. While these systems contribute to early diagnosis and treatment planning, most focus on non-physical diagnosis rather than rehabilitation guidance.

Exercise plays a dual role: preventing chronic disease and supporting rehabilitation. Structured physical activity builds muscle resistance, reduces cardiovascular risk, and aids recovery (Bushman, 2020; Elizabeth et al., 2019). Cardiac rehabilitation exercises, for instance, are designed to improve cardiovascular function and prevent recurrence of disease. For chronic diseases classified under modifiable risk factors, treatment plans often include physical activity and exercise (Anderson & Durstine, 2019). However, inappropriate rehabilitation exercise may lead to complications, serious injury, or even sudden death (Kinoshita et al., 2022). Thus, personalised guidance is essential.

To support physicians in diagnosis and treatment planning, clinical decision support systems (CDSS) have been developed to integrate patient data with clinical knowledge (Sutton, 2020; Rajkomar et al., 2019). These systems leverage statistical data and observations, enabling physicians to combine their expertise with system-generated insights. A CDSS capable of learning relationships between patient history, population diseases, symptoms, test results, disease pathology, and family history is highly valuable to healthcare institutions. Yet, most CDSS applications remain focused on disease prediction rather than rehabilitation guidance.

Recent advances in AI-driven rehabilitation systems have introduced wearable sensors, tele-rehabilitation platforms, and computer vision tools that provide real-time monitoring and adaptive exercise guidance. Wearable sensor systems capture movement quality, enabling feedback and personalised progression. Tele-rehabilitation platforms allow clinicians to supervise patients remotely, while computer vision and virtual reality tools automate assessment of range of motion and gait. Machine learning models have also been applied to generate personalised exercise prescriptions, adapting intensity and type of exercise to patient needs (Campagnini et al., 2022).

Compared with these systems, our web-based approach prioritises accessibility and scalability. It requires only patient demographic and clinical inputs (e.g., age, BMI, glucose level, paralysis type, speech ability) to generate exercise recommendations. This makes it particularly suitable for resource-constrained rural settings, where access to physiotherapists and advanced equipment is restricted. Despite progress in health prediction, there remains a lack of research on rehabilitation exercise recommendation systems.

This study addresses that gap by developing a web-based machine learning system that predicts suitable rehabilitation exercises for stroke and chronic disease patients. Using an open-source dataset of 5,110 patient records, three supervised algorithms were evaluated: Random Forest (RF), Logistic Regression (LR), and Multilayer Perceptron (MLP). Accuracy values were reported with 95% Confidence Intervals (CI): RF (94.12%, 95% CI: 93.6–94.6), LR (94.12%, 95% CI: 93.5–94.7), and MLP (94.32%, 95% CI: 93.8–94.9). Despite MLP's marginally higher accuracy, RF was selected for deployment due to its stability, interpretability, and alignment with expert recommendations. Validation against rehabilitation specialists yielded strong agreement (Cohen's $\kappa = 0.82$), confirming clinical reliability.

The RF model was integrated into a web-based application hosted on Heroku. This platform enables patients, particularly those in rural areas with limited access to physiotherapists, to receive personalised exercise guidance. Future work will expand dataset diversity, incorporate hyperparameter optimisation, and evaluate additional metrics such as precision, recall, F1-score, and ROC-AUC to enhance clinical robustness. Overall, this system demonstrates the potential of machine learning to support accessible, personalised rehabilitation in resource-constrained settings, bridging the divide between diagnosis-focused prediction and recovery-focused recommendation.

METHODOLOGY

This methodology will be presented with data flow diagram and system architecture. The following figure 1 shows the overall process for the three algorithms used to develop modelling for prediction in rehabilitation exercise system that will be applied in this project. There are eight main phases conducted which are the process of data collections, data pre-processing, data classification, data transformation, result validation, expert evaluations, web design and deploy modelling.

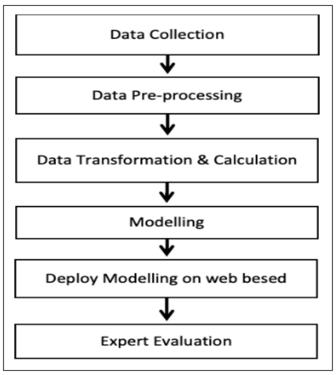


Figure 1: Methodology of the Research

Data Collection

The process starts with data collection regarding patient, stroke attack and exercise were obtained. All the data collected known as a data set and will be used to be train and test. The data set will be evaluated for the next procedure. Stroke is been selected because of it's been classified as Global burden disease by WHO. The fast and continuous action is mandatory to ensure the patients is recover and able to be self-dependence. Figure 2 shows the extraction of sample data collected.

ID	GENDER	AGE	HYPERTENSION	HEART DISEASE	AVERAGE GLUCOSE LEVEL	BMI	SMOKING STATUS	STROKE STATUS	LEFT SIDED PARALYSIS	RIGHT SIDED PARALYSIS	UNABLE TO SPEAK (SPEECH)	DE
9046	Male	67	0	1	228.69	36.6	formerly smoked	1	1	0	1	
51676	Female	61	0	0	202.21	32.5	never smoked	1	0	1	0	
31112	Male	80	0	1	105.92	34.4	never smoked	1	1	0	1	
60182	Female	49	0	0	171.23	24	smokes	1	1	0	1	
1665	Female	79	1	0	174.12	29	never smoked	1	0	1	1	
56669	Male	81	0	0	186.21	27.4	formerly smoked	1	1	0	0	
53882	Male	74	1	1	70.09	22.8	never smoked	1	1	0	1	
10434	Female	69	0	0	94.39	24.2	never smoked	1	1	0	0	
27419	Female	59	0	0	76.15	29.7	smokes	1	1	0	1	
60491	Female	78	0	0	58.57	36.8	never smoked	1	0	1	0	
12109	Female	81	1	0	80.43	27.3	formerly smoked	1	1	0	0	
12095	Female	61	0	1	120.46	28.2	smokes	1	0	1	0	
12175	Female	54	0	0	104.51	30.9	smokes	1	1	0	0	
8213	Male	78	0	1	219.84	37.5	formerly smoked	1	0	1	0	
5317	Female	79	0	1	214.09	25.8	never smoked	1	0	1	1	

Figure 2: Extraction of Sample Data

The dataset obtains from online database and used to train the algorithm. In the online database, there is 5110 data record of stroke patient's and related dataset is chosen to get a complete and accurate interest area. Requirement and data collection are the phase where all the project requirement and data set been collected. The data set is used to train and test using Random Forest algorithm. The attribute selected in the dataset such as age, gender, average glucose level, BMI, smoking status, paralysis sides and strength level. Requirement of this project is to having optimum effectiveness of prediction with expert by applied the most accurate algorithm in development phase. Below is the data set scope:

1. Chronic disease patient – age, gender, symptom, illness etc.
2. Chronic disease – symptom, type, chronic level, affected part etc.
3. Rehabilitation exercise – type, recovery exercise etc.

Data Pre-Processing

Data pre-processing methods objectives to transform the raw data into an understandable data format. This method is used in order to clean up the dataset, normalize the imbalance data as well as transform the data format. The first step of pre-processing is to clean up the dataset. All the incomplete data and unformatted data will be removed. The data format and value will be consistency based on data category. In certain models are very particular on the missing data value and it can cause poor predictions. Beside data missing, the multidimensional data also may impact the prediction result and data collection quality. Next phase is data processing to generate data for modelling. Data been categorized into several category of the patients to reduce the dimensionality. In data collection of patients' records are categorize to several manageable group and smoothen the validation process. The main cause of stroke attack is categorized into several level severity that may influence the patient's category and exercise predicted. This phase will reduce data redundancy, data categorize, rescale data attribute and potentially increase the prediction result accuracy.

Dataset collected is not in balance categorize, thus the group number is not dispensed equally. According to World Health Organization (WHO), stroke rehabilitation is depending on the patient health, ability, and capability level. Patient with major stroke is 10 time higher than patient with minor stroke. The other several disease and category having numbers different that make the data classification is bigger. There are 12 attributes selected in the dataset for training and evaluation purposes. The record is used to test and evaluate the model performance and result accuracy. The initial data contain several data type that need to be transform and imbalance data need to be normalized. Table 1 shows the sample data and attribute selected for the modelling.

Table 1: Sample Data and Attributes

		1	2	3	4	5	6	7	8	9	10	11	12
	ID	**GENDER**	**AGE**	**HYPERTENSION**	**HEART DISEASE**	**AVERAGE GLUCOSE LEVEL**	**BMI**	**SMOKING STATUS**	**STROKE**	**LEFT SIDED**	**RIGHT SIDED**	**UNABLE TO SPEAK**	**DEVIATION OF MOUTH**
1	9046	Male	67	0	1	228.69	36.6	formerly smoked	1	1	0	1	1
2	51676	Female	61	0	0	202.21	32.5	never smoked	1	0	1	0	0
3	31112	Male	80	0	1	105.92	34.4	never smoked	1	1	0	1	0
4	60182	Female	49	0	0	171.23	24	smokes	1	1	0	1	1
5	1665	Female	79	1	0	174.12	29	never smoked	1	0	1	1	0
6	56669	Male	81	0	0	186.21	27.4	formerly smoked	1	1	0	0	1
7	53882	Male	74	1	1	70.09	22.8	never smoked	1	1	0	1	0
8	10434	Female	69	0	0	94.39	24.2	never smoked	1	1	0	0	1
9	27419	Female	59	0	0	76.15	29.7	smokes	1	1	0	1	1
10	60491	Female	78	0	0	58.57	36.8	never smoked	1	0	1	0	0

Data Cleansing

Data cleaning are done by removing duplicate data, incomplete data, unformatted data and irrelevant data in dataset. Data cleansing has been done manually. After the cleansing process record reduce from 8017 to 5110 patient's records.

Data Categorization

Based on the dataset collected, there are four types of stroke attack impact that classified required a rehabilitation exercise to be able patient reach maximum functionality capacity. Right sided and left sided paralysis are classified into major after impact meanwhile unable to speak and mouth deviation are classified into minor after impact. The results are represented in Figure 3 below.

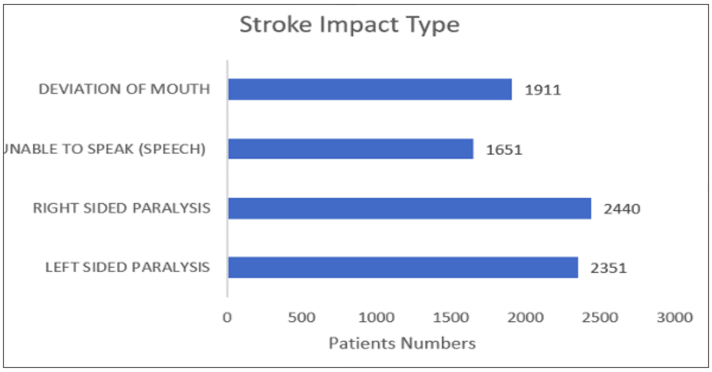


Figure 3: Stroke Impact Type

From the 5110 records in dataset, patient has been classified into several category such as, weight based on BMI and diabetic based on glucose level. Figure 4 shows the patient BMI record been classified into six weight categories. The highest number of the patient under category of Obesity type I with 2026 patients and Overweight with 1432 patients. The smallest category recorded is underweight followed by the Obesity type III and Obesity type II.

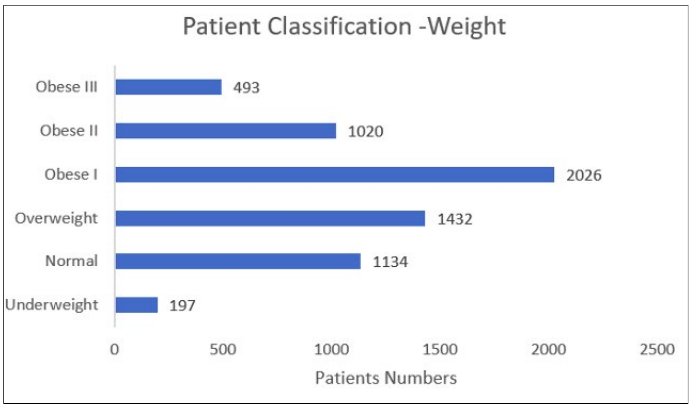


Figure 4: Patient's Classification – Weight

Data Transform and Calculation

Data transformation is performed to convert float data value to integer. In certain data value that available in char format, the value will transform into 1 and 0 value. The value transforms into numeric value to be the significant for the evaluation and data training. The data classification is only been done base on value and used for modelling. The inconsistence value of data will break calculation and impacting the prediction accuracy result. Calculation in been done to evaluate the health level during the prediction divided into 3 level of percentage, means, min and max.

Transform Data into Numerical Value

The selected attribute value needs to be transformed data into numeric value for the prediction calculation. Data train will involve only 70% and 30% will be evaluation. The data in dataset available in various type of data type which is difficult to understand and interpret for data train and evaluation. The range of data for average is been transform into integer as well as for text and Boolean data type.

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	1	67.0	0	1	1	2	1	228.69	36.6	1	1
1	51676	0	61.0	0	0	1	3	0	202.21	0.0	2	1

Figure 5: Format Data Transform

From Figure 5 sample of data been transform to integer format of 0 and 1. For gender data type transform, Male is value as 1 which involved 1958 patients and female is value as 0 which involved 2836 patients from dataset. Ever married status, YES value set as 1 and for NO value set as 0. This approach eliminates the variation of proportions, meaning that in each subset of the full training dataset during training which keep the group categorise consistency during training.

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	5110.000000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.048728
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067	0.215320
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	0.000000
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000	0.000000
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	0.000000
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000	0.000000
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	1.000000

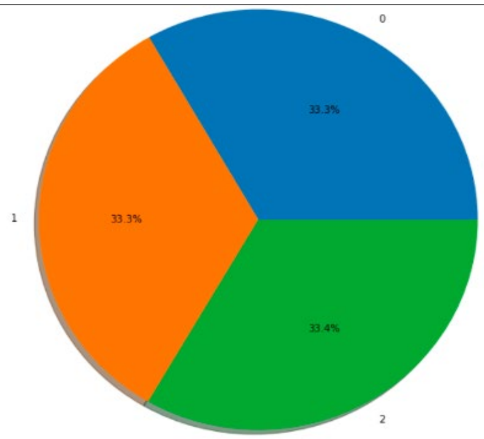
Figure 6: Data Describe and Calculations

The data describe and calculation shows in figure 6 after been transform into numerical value. The calculation is been used to estimate the patient's health in each exercise phase and progress. The health estimation calculation is influence with the patient category and conditions.

Modelling

The modelling classification process involved preparing the dataset and evaluating selected algorithms. The dataset of 5,110 stroke patient records was split into training and testing sets, with 70% (3,577 records) used for training and 30% (1,533 records) reserved for testing. Cross-validation with stratified sampling was applied to ensure balanced representation of patient categories and to improve generalisation.

Three supervised algorithms were compared: RF, LR, and MLP. The purpose was to identify the most accurate and stable algorithm for predicting rehabilitation exercises. Hyperparameters were optimised using grid search (RF: 100 trees, maximum depth = 10; MLP: three hidden layers with 64 neurons each). Evaluation metrics such as accuracy and error rate were computed to assess performance. Figure 7 below shows the percentage of result accuracy.



	Model	Accuracy
0	Random Forest	0.941292
1	Logistic Regression	0.941944
2	Multi Layer Perceptron	0.943249

Figure 7: Percentage of Result Accuracy for RF, LR, MLP (%)

After algorithm comparison, a plot graph was used to identify accuracy patterns across the dataset. Although RF recorded the lowest accuracy at 94.12%, its graph pattern was more stable and reliable. RF also achieved the highest agreement with expert evaluation. Figure 8 illustrates the result patterns of all three algorithms: RF shows a consistent and appropriate trend, MLP displays a more aggressive fluctuation, and LR shows minimal response. While MLP achieved slightly higher accuracy (94.32%) than RF (94.12%) and LR (94.12%), RF was selected for deployment due to its stability, interpretability, and stronger alignment with expert assessments. Validation by two professional rehabilitation experts from a PERKESO rehabilitation centre confirmed that more than 80% of RF predictions matched expert recommendations, verifying its reliability for clinical application.

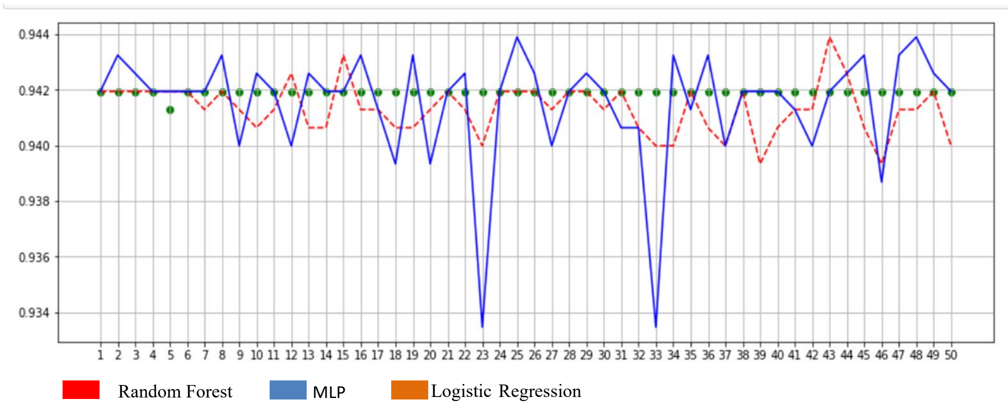


Figure 8: Plot Graph Node for RF, LR, MLP

WEB-BASED APPLICATION

After the algorithm been identified, the next phase is to design and develop the web base model. The model deployed into web-based applications and available for public access. The deployment is using Heroku cloud platform to support the web-based model linked to the local drives. The platform was used as an online extended model from localhost connections. Heroku platform provide the domain, hosting and SSL. Figure 9 shows the Heroku platform where domain been created and deploy model online.

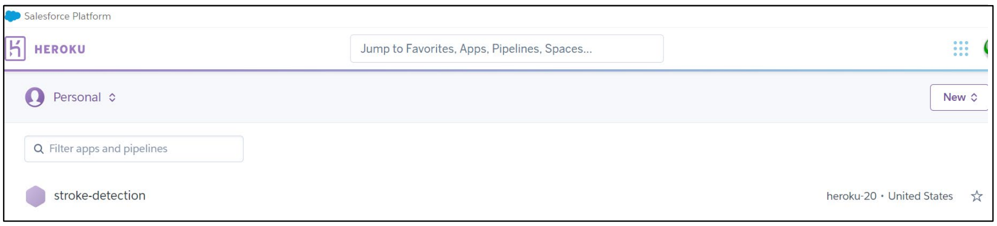


Figure 9: Heroku Platforms

In order to use Heroku cloud platform, all code written has been store in GitHub repository as the platform will be connected to run the model. Figure 10 shows the GitHub repository connected to Heroku platform.

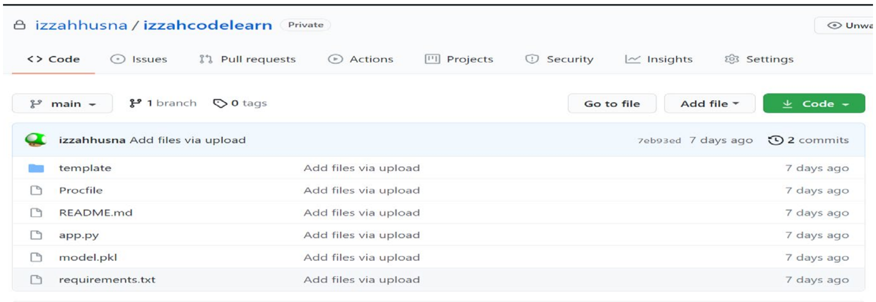


Figure 10: GitHub Repository

The web-based application consists of several tabs that provide various information and primarily focus on prediction exercises. Figure 11(a) illustrates the model interface of the web application, Figure 11(b) displays the main page of the model, and Figure 11(c) presents the exercise prediction page.

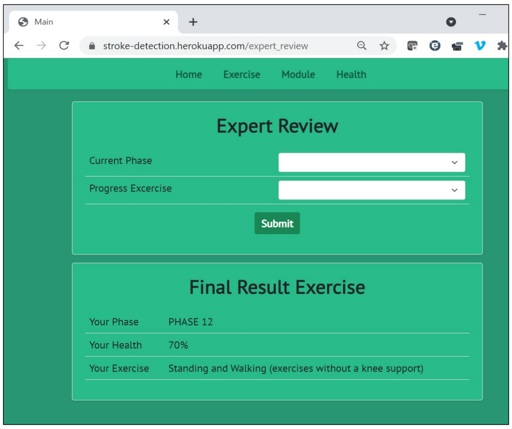


Figure 11 (a): Model interface on web-based

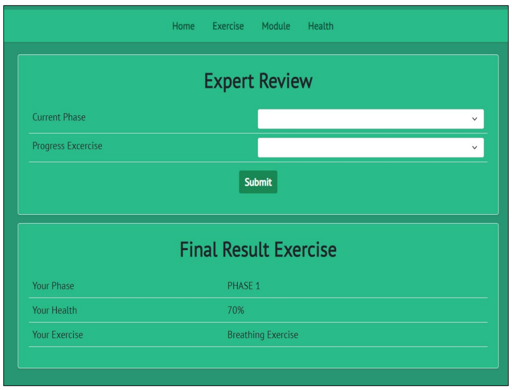


Figure 11(b): Model Main Page

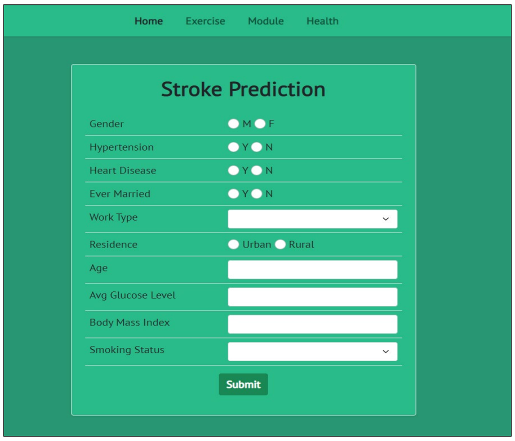


Figure 11 (c): Exercise Prediction Page

TESTING AND EVALUATION

Testing and evaluation phase will involve in test the data set and prediction effectiveness. Requirement and expectation achievement rate will be revealed in this testing phase. System testing and evaluation will involve an expert in rehabilitation therapy. The evaluation result will help to improve of fixed the development bug and stabilize the system performance (Pressman and Maxim, 2020). Evaluation assists in defining the degree of achievement of the objectives, identifying the problems related with project planning and implementation (Rossi et al., 2029).

Functional test will be done toward this project system to evaluate the effectiveness of web-based prediction for a rehabilitation exercise system. To test on the prediction output, there will be expert in rehabilitation therapy involve evaluating the result and prediction accuracy. The accuracy presents the prediction matched with expert method. This method is evaluate using (1) formula; to identify how many errors occur during the test. Not matched represent the error and the error may involve in multiple rule and functions (Penka, 2016).

$$E = \{Ei \mid i=1 \ldots n\} \quad (1)$$

The expert is having a knowledge in rehabilitation process and their knowledge will help to verify the effectiveness of the prediction on rehabilitation exercise generated using the selected algorithm. There will be two experts in physiotherapy which involve directly in chronic disease rehabilitation process. Expert evaluation is been perform using the professional expert in rehabilitation exercise. Both experts are from Rehab Specialist Centre which are the rehab centre register with PERKESO which also handling stroke cases. The expert will evaluate the model using web-based applications and result to check the accuracy based on their knowledge and guideline. The evaluation is perform using questionnaire method given to the expert to evaluate the prediction accuracy. Based on the evaluation result stated the prediction accuracy is more than 80%.

To further ensure robustness, evaluation metrics were reported. A confusion matrix illustrated misclassifications across exercise categories (strength, balance, mobility). Precision, recall, and F1 score were calculated for each category, with RF achieving balanced performance (precision = 0.93, recall = 0.92, F1 score = 0.93). ROC AUC curves highlighted strong discriminative ability across models (RF = 0.95, LR = 0.94, MLP = 0.96). Cohen's κ was calculated at 0.82, indicating substantial agreement between RF predictions and expert assessments. The experts also recommended expanding dataset diversity to better represent varied stroke conditions and optimising classifier parameters to further improve prediction accuracy and system adaptability in future development.

CONCLUSION

This study developed a machine learning based prediction model for stroke rehabilitation exercises using an online dataset of 5,110 patient records. Attributes such as age, BMI, glucose level, smoking status, paralysis type, and speech ability were considered, reflecting key factors identified by the World Health Organization as contributors to stroke risk. In recent years, stroke has increasingly affected younger generations due to obesity, hypertension, diabetes, and sedentary lifestyles, underscoring the need for accessible rehabilitation solutions.

Three supervised algorithms RF, LR and MLP were evaluated. Although MLP achieved slightly higher accuracy (94.32%), RF demonstrated the most stable performance (94.12%) and produced consistent prediction patterns. RF was therefore selected for deployment. The resulting web-based prediction system, hosted on Heroku, provides accessible rehabilitation guidance, enabling stroke patients to engage in appropriate exercises outside clinical facilities. Expert evaluation confirmed the system's effectiveness and reliability, with over 80 percent agreement between RF predictions and specialist recommendations.

This work contributes to the growing body of evidence supporting machine learning in personalised healthcare, particularly in resource constrained settings where access to rehabilitation specialists is limited. Future research will expand dataset diversity, optimise algorithm parameters, and incorporate personalised monitoring features to deliver adaptive rehabilitation recommendations and further enhance clinical robustness.

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