

Forecasting of Cognitive Neurological Aspects Using Machine Learning Ensemble Algorithms

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Abstract: *The physical and mental capacities of healthy older persons frequently deteriorate with age. Individual differences are observed in the degree of these behavioral and neurocognitive impairments. A reserve, or defense mechanism, that strengthens the brain's resistance to age - related damage, may be developed by intellectually demanding activities and lifelong experiences, according to the Neurocognitive Hypothesis in cognitive neuroscience. The differences in the degree of visible brain damage and its functional consequences have been well explained by this statistical model. In summary, the statistical modelling presented here illustrates how neurocognitive reserve affects age - and individual - related changes in brain architecture, neural networks, and neural activation patterns. The modelling is based on behavioral and neuroimaging findings. Furthermore, we report preliminary results from structural and functional neuroimaging that lend credence to the idea that neurocognitive reserve functions as a neural resource, reducing the impact of cognitive decline resulting from both the aging process and neurological and psychiatric diseases. In summary, the neurocognitive model provides a dynamic view of resilience and our ability to adjust to brain illness and damage as we age, as predicted by statistical models, even though the processes underpinning the model are still not fully understood. Through predictive modelling, future studies should try to identify the unique elements that support neurocognitive reserve's positive benefits in delaying rapid cognitive decline and fostering psychological resilience in old age.*

Keywords: Cognitive Neuroimaging, Resilience, Correlation Studies, Ensemble algorithms

1. Introduction

The idea of aging is becoming more and more common place throughout the globe. There are differences across countries in the world. Until now, this idea and the exact age at where the older period begins have not completely defined. Pandits neurological aspects agree over the age at which the old should begin to live, and they have not yet agreed upon an exact figure for the aged population. According to certain research, the elderly are defined as being 60, 65, or even 80 years of age or older, at which point the fall of phenomena takes place. This phenomenon lowers the level of reliance, impairs people's physical and mental well - being, and lowers the self - esteem and quality of life of the elderly population. The reduction in the birth rate, advances in healthcare and medical education, advancements in technology, improved diet, and medical conditions have all contributed to the recent increase in the population's life expectancy. According to estimates, there will be 426 million senior people in the world by 2050, increases from 143 million in 2019. Furthermore, in 2100, the average lifespan will rise to 82 years old. According to Rowe and Kahn, the neurological aspects model is a comprehensive approach that addresses human lifestyles in three areas: (1) Low risk of physical disease and related disorders (2) High ability to perform both mentally and physically; and (3) Active engagement in social behavior of life. The Successful Aging (neurological aspects) idea is widely accepted by people worldwide and has improved the quality of life for the aged as a result of variables such as an expanded older population, longer life expectancy, and attention to assist the elderly from diverse physical, mental, and social problems. Understanding this idea and enhancing the quality of life for the elderly have received a lot of attention as a result of this trend (4). The neurological aspects notion was explained by

a few hypotheses that surfaced in the 1960s and 1970s. neurological aspects was defined by Cumming & Henry's disengagement hypothesis as older people participating in social activities more often (5). Havighurst served as a representative of the activity hypothesis, which examined interacting with the elderly in the community. Atchley is a representative of the continuity hypothesis, which explains how older people can engage in social and personal activities as late in life as they would want (6). A qualitative approach to the aging era involves identifying the features of a successful aging pattern (7). As a result, lifestyle characteristics and environmental factors may be thought of as predictive factors in predicting the neurological aspects, which improves the quality of life for the aged (8). They held that aging may also be influenced by lifestyle choices and that genes had no bearing on biological aging (9). The greatest gerontologists in the world have also investigated and validated this theory (10). Higher physical performance, less physical and mental problems, and improved social settings are all associated with using a model to predict neurological aspects in the early stages of old or even middle - aged people's lives. These factors increase the likelihood of success in these individuals' final years of life (11). Predictive models may be useful in the diagnosis, prognosis, and treatment of a variety of medical illnesses, including mental, cognitive, and physical problems (12). The prediction models in the neurological aspects and QoL in the aged based on physical and cognitive characteristics have been the focus of the investigations. The social variables influencing the neurological aspects prediction have received little attention from them (13). Senior social activities are important and should be taken into account in neurological aspects (14). neurological aspects improvement may be predicted more accurately by the Machine Learning (ML) of the predictive models (15). Taking into

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consideration of an individual's physical, mental, and social characteristics, this study attempts to develop the neurological aspects model by utilizing a variety of machine learning approaches.

2. Literature Review

According to a study of the literature on forecasting cognitive neuroscience and successful aging, there has been a noticeable increase in the use of machine learning techniques within the subset of artificial intelligence in recent years. Researchers have developed a variety of strategies to improve accuracy. Furthermore, a number of studies have looked into how these technologies might be used to impact the historical data from the past and other important aspects of cognition forecast.

“This study employed machine learning algorithms to predict cognitive decline using neuro - imaging data and cognitive assessments. The authors demonstrated that models incorporating features from structural MRI and cognitive tests achieved high predictive accuracy for future cognitive decline.” [1] [2] [3] “The study used longitudinal data to develop statistical models predicting cognitive aging trajectories. Results indicated that individual differences in cognitive decline can be predicted by baseline cognitive function and demographic variables.” [4] [5] “The research focused on developing predictive models for cognitive resilience, particularly how certain interventions or lifestyle changes could predict recovery or maintenance of cognitive function.” [6] [7] [8] “This publication assessed various cognitive interventions' effectiveness using predictive models. The study highlighted how cognitive training and lifestyle changes can influence cognitive health outcomes.” [9] [10] “The study applied time - series analysis to forecast future trends in cognitive health based on current data and demographic trends” [11] [12] [13]. Predictions include changes in prevalence rates and healthcare needs. ” [14] “This paper also examined how socioeconomic factors influence cognitive health and used forecasting models to predict future impacts based on current socioeconomic trends.” [15] [16]

“The research emphasized the need for longitudinal studies to understand the long - term effects of predictive models on cognitive aging outcomes and intervention efficacy.” [17] “This research focused on predictive models for cognitive decline using longitudinal data, including factors such as baseline cognitive function, demographic variables, and health indicators.” [18] “This study developed forecasting models to predict the effects of cognitive training programs on various cognitive domains. It emphasized the potential for personalized interventions based on individual profiles.” [19] “The study focused on predicting cognitive load during complex tasks using statistical and machine learning models. It explored how task demands and individual differences affect cognitive load.” [20]. In the synopsis, the literature study deep dives into a distinguished assortment of approaches for predicting the cognitive and successful aging, while also including elements of artificial intelligence such group modeling techniques. Scholars continue to investigate novel technical strategies aimed at improving prediction accuracy and identifying the obstacles faced by neurological

sciences.

3. Materials and Methods

This study used a descriptive and applied methodology and was conducted in the following two steps: 1. Description of the data: The database, which was collected from January 2017 to January 2021 in research centers from Hyderabad City contained 515 and 950 records related to females and males, respectively. We used the 1465 records in this study to investigate the most significant factors affecting the neurological aspects and to build the prediction model. Characteristics of Predictors Sociodemographic characteristics that fall under the category of persistent illnesses include age, gender, literacy level, marital status, kind of profession, source of money, monthly income, and insurance status. This category of variables is further subdivided into depression, convalescences, liver, kidney, eye, bone, muscle, and other functional illnesses, diabetes, high blood pressure, cancer, and cardiovascular accidents (CVA). Psychosocial and behavioral aspects A neurological aspects has the best quality of life (grades higher than 70 in the SF36 questionnaire which was ranged from 0 to 100), best life neurological aspects satisfaction (grades ranging from 20 to 35 on the Diener Life Neurological aspects satisfaction Scale which was ranged from 5 to 35), and a pleasure level of personal independence (the grade ranging from 90 to 100 according to the Barthel index). Below is a description of the factor that determines these variables. Life quality: This variable can assess health and life quality. In 1992, Ware and Sherborne designed it. Eight contexts—physical and social ability, physical and cognitive active involvement, psychological health, evaluation vivacity, physical discomfort, and overall health status—were included in the 36 surveys. Furthermore, the 36 - SF is composed of two broad assessments of social, mental, and physical health called the total mental and physical component score. In these cases, the topic might be anywhere between 0 and the older population has a superior quality of life, according to the larger quantities. This questionnaire's validity and reliability have been examined and supported across Hyderabad neurological aspects sample populations. People's level of individual independence is determined using the Barthel Index. It calculates each person's physical health based on 10 questions. This measure, which ranges from 0 to 100, indicates a person's proficiency in a variety of everyday function areas. The range from 0 to 20 represented those who were very dependent, from 20 to 60 represented complete dependence, from 61 to 90 representing medium dependence, from 99 to 91 representing little dependence, and from 100 representing complete independence (33). Contentment with the Life Scale (SWLS) Diener et al. introduced this criterion. It had five items that evaluated the mental aspects of wellbeing and health. Every condition has seven possible answers, ranging from strongly neurological aspects agree to strongly agree. A higher score indicates greater life neurological aspects satisfaction. According to Bayani et al. (2007), the validity of this questionnaire was supported. Lifestyle: The entire grade received determines the lifestyle. To get it, one must provide a rating between 42 and 98 for an awful lifestyle, 99 to 155 for a medium lifestyle, and 156 to 211 for a happy living. It assesses

physical activity, leisure, social and interpersonal interactions, stress management, good eating, and exercise 2. Data analysis: We carried out the data analysis after identifying the key variables influencing the neurological aspects and getting our dataset ready. Preprocessing the dataset, choosing and putting into practice the ML models, and evaluating to determine which prediction model has the most impact on the neurological aspects is all included in this stage. During the preparation stage, we first fixed discrepancies in our database by merging the numerous datasets from different senior centers. We also cleansed our data. In this regard, by figuring out the quantiles of our data point distributions, we were able to locate and smooth out any noise in our datasets. Records with that missing class were removed from the data points in the output class that had missing values. In order to fill the gaps in the features predicting the neurological aspects, we also imputed the missing values using regression approaches, which predict the missing values by other available values in attributes. The trimmed mean was used to replace missing values in numerical data with the least level of bias. Third, we employed the Synthetic Over neurological aspects sampling Technique to balance the quantity and avoid form biases when assessing the algorithms' performance due to the unequal distribution of neurological aspects samples among the output classes. Secondly, we applied the Feature Selection (FS) approach to refine the dataset and lower its dimensions. The best variables are chosen by FS, which also reduces the size of the dataset. Potential advantages of this method include the elimination of redundant data, prevention of algorithm overfitting, acceleration of machine learning training, decrease in data redundancy, and improved learning accuracy. In this investigation, we employed the Chi - square independence test (χ^2) to ascertain the correlation between every element influencing the neurological aspects prediction and neurological aspects. In

this sense, the factors that showed a link at $P < 0.05$ were deemed statistically significant. The study excluded other variables that failed to neurological aspects satisfy this statistical threshold. We utilized the python, R and SPSS (Statistical Package for Social Sciences) software's to carry out the machine learning process in order to produce the most popular model for predicting adult performance based on the best variables influencing success as determined by statistical analysis. Since three ML algorithms are more often employed and perform better than other algorithms in recent research, they were chosen and put into practice in this way.

Random Forest (RF): A well - known machine learning approach for building decision models is the RF decision tree. In order to categorize the dataset neurological aspects samples, this approach is composed of several subtrees. The Classification and Regression (CART) approach is used to build the RF algorithm trees without any pruning. The variables in this method are chosen at random to initiate the splitting process. The RF's neurological aspects sample classification capacity was enhanced by this feature, particularly when dealing with huge dataset dimensions. This technique employs a voting procedure to categorize the neurological aspects samples with high accuracy, making it appropriate for high dimensional datasets with several factors. Put differently, this algorithm's performance is shared by the majority of its sub - trees along with its improved capacity for categorization. This approach may achieve excellent accuracy even with noisy data in huge datasets by dividing the neurological aspects samples across subtrees with distinct dataset properties, hence avoiding the overfitting of the algorithm. In general, the benefits of RF may be characterized as flexibility, resistance to noisy data, and speed and accuracy throughout the training process.

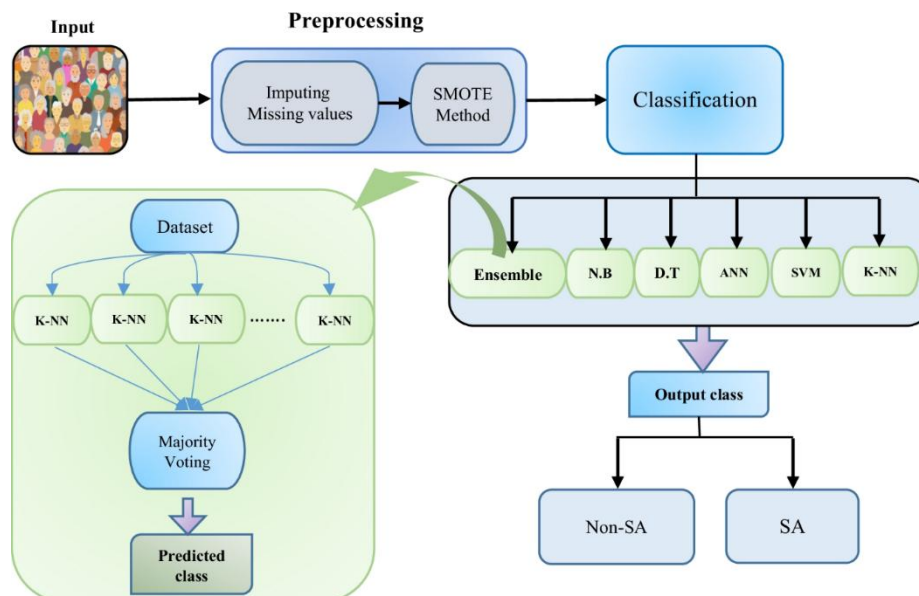


Figure 1

Ada - boost: An ensemble category boosting approach that uses weak classifiers to classify instances concurrently and find and eliminate mistakes in the classified cases in each classifier in turn is known as adaptive - boost, or Ada - boost. Among the many benefits of this algorithm are its

high accuracy generalizability, its efficient calculation ability, its adaptability for a wide range of jobs involving complex data, its ease of adaptation, and its ability to integrate with other algorithms.

SVM (Support Vector Machine): One of the techniques for classification and regression that uses the hyperplane notion to complete the classification problem is the Support Vector Machine (SVM). The low dimensional data points are mapped by this technique to the higher dimensions in order to identify the situations, which are then utilized by the kernel functions. To classify SVM algorithms into linear and non - linear kinds, different kernel types are applied to different datasets based on the data's complexity.

We used the confusion matrix (Table 1), along with the sensitivity, specificity, accuracy, F - Measure and AUC (area under the ROC (Receiver Operator Characteristics) curve obtained from the confusion matrix, to evaluate the performance of selected machine learning algorithms in order to determine the best model to determine the success among the elderly. The decision models accurately identified the successful and failed instances as True Positive (TP) and True Negative (TN) in Table 1. The adults who are successful and those who are unsuccessful that the algorithms have mistakenly classified as False Negatives (FN) and False Positives (FP) in Table 2. In this study, the algorithms were trained, tested, and validated on 70%, 20%, and 10% of the neurological aspects samples, respectively. When assessing the performance requirements, the ten - fold cross - validation was taken into consideration as a means of measuring mistakes.

Table 1

Sensitivity: $TP / (TP + FN)$
Specificity: $TN / (TN + FP)$
Accuracy: $(TP + TN) / (TP + TN + FP + FN)$
Precision: $TP / (TP + FP)$
F1 score: $2TP / (2TP + FP + FN)$

Table 2: Confusion Matrix

	True +	Condition -
Predicted Condition +	TP	FP
Predicted Condition -	FN	FN

Where,

FN: False Negative = truth = 1 & prediction < threshold,

FP: False Positive = truth = 0 & prediction >= threshold,
 TN: True Negative = truth = 0 & prediction < threshold, and
 TP: True Positive = truth = 1 & prediction >= threshold.

4. Results

Fifteen records (1%) representing successful and failed instances were eliminated from the research after the records in the output class with missing data were eliminated. As a result, 1465 records were analyzed using the SMOTE approach; 746 and 719 cases, respectively, were linked to failed and successful instances. Table 3, Table 4 and Table 5 displays the outcomes of the Chi - square independence test and also P - values based on the particular variables which includes about encodes such as demographic cycle variables, different forms of diseases variables, health and social relations variable. Overall, Table 6 insights about the Quality of life, Physical activities and also Performing activities to forecast the successful aging.

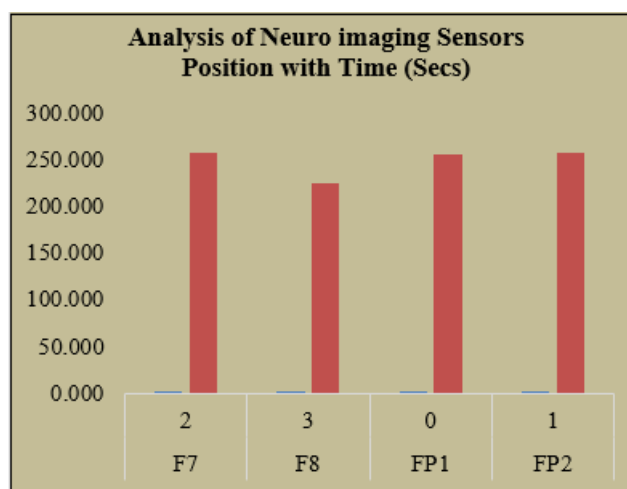


Figure 2

The above Fig2 explains about the analysis of neuro imaging sensors position with the time frame while executing for all the patients suffered with the cognitive neuro science who has highly sensor valued channel - based condition can grasp the things within a short span of time. The fig also mentioned about the sample based number lies between 0 - 255.

Table 3: Results of Chi Square test of all Variables

Variables	Variables encode	Frequency	Chi - square	P - value
Age	60 - 70 (1)	60 - 70 (964)	3.943	0.0139
	70 - 80 (2)	70 - 80 (371)		
	>80 (2)	>80 (130)		
Sex	Female (1)	Female (758)	20.441	<0.001
	Male (2)	Male (707)		
Educational Level	No literacy (1)	No literacy (861)	6.113	0.106
	Elementary (2)	Elementary (338)		
	Diploma (3)	Diploma (172)		
	Academic (4)	Academic (94)		
Marital Situation	Married (1)	Married (1014)	2.019	0.568
	Single (2)	Single (39)		
	Divorced (3)	Divorced (23)		
	Windowed (4)	Windowed (389)		
Occupation type	No job (1)	No job (240)	3.090	0.378
	Housekeeper (2)	Housekeeper (605)		
	Retired (3)	Retired (402)		

	Self - employment (4)	Self - employment (218)		
Income level	Under poverty line (1) On poverty line (2)	Under poverty line (1134) On poverty line (331)	15.546	<0.001
Family Support	Have (0) Haven't (1)	Have (675) Haven't (790)	14.121	0.01
Insurance Situation	Have (1) Haven't (2)	Have (1293) Haven't (172)	0.005	0.946
High Blood Pressure	Have (1) Haven't (2)	Have (1124) Haven't (341)	82.943	<0.001
Cardiovascular disease	Have (1) Haven't (2)	Have (472) Haven't (993)	30.832	<0.001

Table 4: Results of Chi Square test of all Variables

Variables	Variables encode	Frequency	Chi - square	P - value
Bone diseases	Have (1) Haven't (2)	Have (790) Haven't (675)	9.067	0.003
Renal diseases	Have (1) Haven't (2)	Have (1) Haven't (2)	0.444	0.505
Liver diseases	Have (1) Haven't (2)	Have (143) Haven't (1322)	4.331	0.037
Muscle diseases	Have (1) Haven't (2)	Have (887) Haven't (578)	24.539	<0.001
Depression	Have (1) Haven't (2)	Have (449) Haven't (1016)	5.864	0.015
Convalescences	Have (1) Haven't (2)	Have (78) Haven't (1387)	2.445	0.118
Eye diseases	Have (1) Haven't (2)	Have (286) Haven't (1179)	0.197	0.657
Diabetes	Have (1) Haven't (2)	Have (738) Haven't (727)	58.542	<0.001
Cancer	Have (1) Haven't (2)	Have (136) Haven't (1329)	12.647	<0.001
Other diseases	Have (1) Haven't (2)	Have (68) Haven't (1397)	0.828	0.661
Activity daily living	Have (1) Haven't (2)	Have (876) Haven't (589)	10.225	<0.001
Sporting exercises	Have (1) Haven't (2)	Have (453) Haven't (1012)	8.889	0.03
Exercise duration	Have (1) <0.5 hour Haven't (2) >0.5 hour	Have (778) <0.5 hour Haven't (354) >0.5 hour	14.334	0.021
Exercise type	Hard exercise (1) Soft exercise (2)	Hard exercise (598) Soft exercise (778)	13.336	0.08

Table 5: Results of Chi Square test of all Variables

Variables	Variables encode	Frequency	Chi - square	P - value
Sexual Condition	Healthy (1) Unhealthy (2)	Healthy (525) Unhealthy (940)	7.775	0.01
Tension control capability	Low (11) High (12)	Low (989) High (476)	1.612	0.02
Social relationships with other persons	Weak (9) Strong (10)	Weak (418) Strong (1047)	1.379	0.001
Assessment of the nutritional situation	Fair (1) Good (2)	Fair (923) Good (542)	16.621	0.001
Assessment of the malnutritional situation	Have (1) Haven't (0)	Have (620) Haven't (845)	14.228	0.001
Life Neurological aspectstisfaction	Pleaneurological aspectsnt (1) Unpleaneurological aspectsnt (2)	Pleaneurological aspectsnt (1051) Unpleaneurological aspectsnt (414)	41.028	<0.001
The general explanation of lifestyle	Undesirable (1) Medium (2) Desirable (3)	Undesirable (244) Medium (1203) Desirable (18)	13.188	0.001
General health	Have (1) Haven't (2)	Have (924) Haven't (541)	10.453	<0.001
Assessment of body pain	Have (1) Haven't (2)	Have (674) Haven't (791)	7.42	0.11
Physical dsyfuntion	Have (1) Haven't (2)	Have (370) Haven't (1095)	13.212	0.01
Fatigue	Have (1)	Have (855)	8.260	0.162

	Haven't (2)	Haven't (610)		
Mental dsyfunction	Have (1) Haven't (2)	Have (616) Haven't (819)	32.365	<0.001
Social dsyfunction	Have (1) Haven't (2)	Have (935) Haven't (530)	18.552	<0.001

Table 6: Results of Chi Square test of all Variables

Variables	Variables encode	Frequency	Chi - square	P - value
Quality of life	Low (3)	Low (994)	13.768	<0.001
	High (4)	High (471)		
Physical Activity	Low (1)	Low (1092)	3.655	0.056
	High (2)	High (373)		
Performing debarment activities when occurring disease	Low (7)	Low (949)	4.096	0.027
	High (8)	High (516)		

Based on the data presented from the tables about the variables related to age, sex, income level, family support, high blood pressure, cardiovascular diseases, bone diseases, liver diseases, muscle diseases, depression, diabetes, cancer, activity in daily living, sporting activities, duration of exercise, sexual condition, ability to manage tension, social relationships with others, assessment of nutritional status, assessment of malnutrition status, life neurological aspects satisfaction, general explanation of lifestyle, general health, physical, mental, and social dysfunctions, quality of life, and performing debarment activities when diseases occurring

achieved a statistically significant relationship with neurological aspects as the output class. The study excluded the following variables due to lack of statistical support for their inclusion: educational level, marital status, type of occupation, insurance status, eye diseases, other diseases, renal diseases, convalescences, exercise type, assessment of body pain, fatigue, and physical activity with the independence chi - square at $P > 0.05$. Table 3 displays the outcomes of the neurological aspects samples' classification using the confusion matrix.

Table 7: Results of the Confusion Matrix of Selected Models

Algorithm	Hyperparameter	TP	FN	FP	TN
Random Forest	Ensemble Decision Tree type= "Decision Stump"	679	67	12	707
	Maximum depth = "8"				
	Number of iterations = "20"				
	Number of execution slots = "2"				
	Number of randomly selection features = "2"				
Ada - boost	Number of decimal places = "2"	637	109	90	629
	Number of iterations = "15"				
	Classifier="Rep - Tree"				
	Weight Threshold="100"				
	Use neurological aspects sampling="True"				
SVM	Kernel Type = "RBF"	585	161	108	611
	C="15"				
	Gamma="1.0"				
	RBF Gamme="0.1"				
	Regression precision ="0.1"				

From Table 7 clearly depicts the results of the confusion matrix of selected models, the RF method with TP = 679, FN = 67, FP = 12, and TN = 707 has performed better than other ML models in classifying the positive and negative situations, as shown by Table 7. The least effective SVM algorithm in this regard was the one with TP = 585, FN = 161, FP = 108, and TN = 611. Also, presents the findings on sensitivity, specificity, and accuracy of particular machine learning models. In terms of categorizing successful and failed cases, the RF model with sensitivity = 0.91, specificity = 0.98, and accuracy = 0.95 performed the best among other ML models and the adaboost with sensitivity = 0.85, specificity = 0.87, and accuracy = 0.86 both performed favorably in this regard.

The tables displays the F - measure results for each ML model in the train, test, and validation modes in all states of the train, validation, and test modes, the RF model with F - train=0.98, F- validation=0.95, and F- test=0.9 performed better than other ML models. All three ML models' F -

measures were evaluated, and the findings generally indicated that the test mode's F - measure rate has not decreased significantly. As a result, the training neurological aspects sample data has not overfit any of the algorithms. Additionally, in the training, test, and validation modes of the algorithms, the Ada - boost with F- train=0.89, F- validation=0.87, and F- test= 0.81 and the SVM with F- train=0.85, F- validation=0.82, and F- test=0.81 shown favorable performance. The vertical and horizontal vertices, which range from 0 to 1, stand for sensitivity and 1 - specificity, respectively. The RF models was closest to the specificity vertices as per Table 7. The RF model that was able to distinguish between successful and unsuccessful cases had the highest AUC - train = 0.955, AUC - validation = 0.931, and AUC - test = 0.884 values. Compared to other machine learning models, the results of the selected models, where the SVM model was the closest to the 1 - specificity vertices. Its classification performance was the lowest, with AUC - train = 0.67, AUC - validation = 0.634, and AUC - test = 0.555. The RF model, which performed better than

other ML models in this study in terms of classifying successful and unsuccessful cases associated with the elderly, was determined to be the best model for predicting the NEUROLOGICAL ASPECTS among the elderly. It had the following characteristics: sensitivity = 0.91, specificity = 0.98, accuracy = 0.95, F - train = 0.98, F - validation = 0.95, and F - test = 0.9. A portion of the RF model from which some rules have been extracted and explained. We identified three significant rules with more categorized cases discovered such as NEUROLOGICAL ASPECTS equals 1 if (hypertension = 2) && (life neurological aspects satisfaction = 1); 2. In the event where (diabetes = 2), (hypertension = 1), and (life neurological aspects satisfaction = 1), then NEUROLOGICAL ASPECTS = 1; 3. NEUROLOGICAL ASPECTS equals 0 if (hypertension = 1) && (life neurological aspects satisfaction = 2); The RF model predicts that an aged person will succeed in rule 1 if they have no blood pressure and a neurological aspects level of life neurological aspects satisfaction; 210 occurrences support this prediction. While this rule was deemed ineffective in 41 cases, the majority of cases (precision = 0.83) identified it as successful.

In rule 2, the RF will predict that an aged person is successful if they have high blood pressure, a positive life neurological aspects satisfaction score, and no diabetes. 217 of the 270 examples in the leaf (precision = 0.803) supported this rule. According to Rule 3, the RF model predicts that an older adult with high blood pressure and a miserable existence will be less neurological aspects satisfied than someone who is successful. For this rule, the model accurately categorized 283 out of the 360 classified examples, with a prediction precision of 0.786. Based on the average impurity decrease and the number of nodes utilizing that characteristic in the model, Table 8 displays the relative significance (RI) of parameters for predicting the neurological aspects produced by the RF model.

Table 8

Most important features obtained in the RF model		
Variable	Number of nodes used in RF Model	RI
Lifestyle pleasure	1456	0.4
Quality of life	2618	0.32
Assessment of the nutritional situation	2819	0.3
Diabetes	1300	0.29
CVA	1573	0.28
Life Neurological aspectstisfaction	1337	0.28
Sex	2141	0.28
Tension	2970	0.27
Age	2611	0.27
High blood pressure	1125	0.27
Performing debarment activities when occurring disease	2341	0.27
Bone disease	3020	0.26
Muscle disease	2126	0.26
Interpersonal relationships with others	2714	0.25
Depression	2274	0.24
Insurance situation	1702	0.22
Liver diseases	1536	0.22
Cancer	904	0.17

Table 8 shows that all of the factors connected to the NEUROLOGICAL ASPECTS prediction had RIs between 0.17 and 0.4. Among the variables that were chosen, the

three variables that were thought to have the greatest effects on NEUROLOGICAL ASPECTS were lifestyle enjoyment (RI = 0.4), quality of life (RI = 0.32), and neurological aspect of the nutritional condition (RI = 0.3). The RF model assigned the lowest relative relevance score to the three variables—insurance situation (RI = 0.22), liver illnesses (RI = 0.22), and cancer (RI = 0.17); hence, the model identified these variables as having the least bearing on the neurological aspects prediction.

5. Discussion

Our goal in this study was to use ML models to construct an AI predictive model for neurological aspects. Initially, we went over and extracted the articles related to the elements influencing the neurological aspects. Subsequently, the expert opinions were utilized to determine the most significant criteria, with over 60% of the experts included in this study agreeing on the factors. Second, we performed the Chi - square independence test at $P < 0.05$ to statistically determine the important factors and examine each factor's association to neurological aspects. In the third phase, we chose the suitable machine learning models to apply the model that predicted the neurological aspects after preprocessing the data and identifying the best parameters influencing the neurological aspects. The AB, RF and SVM algorithms were chosen in order to achieve this. Ultimately, by comparing and assessing each ML model's performance across a range of performance metrics, including sensitivity, specificity, accuracy, F - measure, and AUC in all training, testing, and validation stages, the optimal predictive model for neurological aspects is determined. Few research has been done on neurological aspects prediction models thus far, particularly in the ML field. The majority of research has looked at the quality of life (QoL) of the aged and examined the social, psychological, and physical aspects independently. Using machine learning techniques, Cai et al. developed a prediction model for neurological aspects based on the physical parameters. According to their research, the deep learning model performed the best in predicting the neurological aspects, with an AUC of 90%, a specificity of 93.1%, and an accuracy of 83.9%. Additionally, the model (30) identified age, arm curl, sitting and standing for 30 seconds, and reaction time as critical variables influencing the neurological aspects. In addition to the physical aspects, the mental and social elements influencing the neurological aspects prediction are taken into account in our study. Based on these variables, the RF model with sensitivity = 0.91, specificity = 0.98, and accuracy = 0.95 had the highest performance in predicting the neurological aspects. The RF model also identified the variables that best accounted for lifestyle pleasure, quality of life, and assessment of nutritional status. Li et al. used machine learning algorithms to predict the quality of life (QoL) based on physical characteristics, laboratory measures, demographic factors, and healthy habits. They discovered that the most important variables influencing the quality of life are age, walking speed, sleep duration, handgrip strength, body mass index, blood pressure, and length of time spent sitting and standing (55). The social and mental aspects are taken into consideration in addition to the elements that were introduced in the previous study, and the QoL is one of the dimensions that affects the neurological aspects in the

current study. In order to predict cognitive decline in older adults two years later, Kyoung - Neurological aspects Na conducted a study. Age was shown to be the best component derived from the Gradient Boosting Machine (GDM) algorithm, which demonstrated the strongest capacity to predict cognitive impairment with sensitivity = 0.96, specificity = 0.825, and AUC = 0.921 (56). According to the current study, the most important factor for predicting neurological aspects is age (RI = 0.27). Furthermore, in order to create a prediction model for improving older people's quality of life, we identified social, physical, and mental aspects in our study. Byeon used the ANN and Quest algorithms to create a predictive model for senior social participation. In categorizing older people as a social activity, the ANN with AUC= 0.718 and Quest with 0.754 with 10 - fold cross - validation performed reasonably well. The age with NI = 89% and the subjective health state with (Normalized importance) = 100% were stated to be the crucial variables in this regard (57). The new study's inclusion of illnesses that may be present in the elderly and limitations on social and physical engagement made the factors impacting neurological aspects more apparent. Furthermore, a greater number of machine learning models—both ensemble and non - ensemble—are employed to forecast the neurological aspects in senior citizens. The prediction model for utilizing ML models to forecast the neurological aspects has not yet been released. Thus, our study's innovation lay in applying Rowe and Kahn's theory to the physical, mental, and social components in order to construct a model for ML models that predict neurological aspects. As a result, early detection of neurological aspects in the elderly can help them by introducing the solution for people and physical and mental care providers to advance the lifestyle and quality of life in this age group. Our model can predict the success or unsuccess of the people in the earlier periods of the elderly. The likelihood of neurological aspects will rise in the elderly population since mental and physical illnesses will be identified earlier in life.

6. Conclusion

By reducing mental and physical morbidity and boosting older people's physical and social participation, using the neurological aspects prediction model based on ML models can improve their quality of life. This work created prediction models for neurological aspects using the AB, RF and SVM algorithms. The study demonstrates that, among other things, the variables that have the greatest impact on neurological aspects are lifestyle pressure and quality of life. Based on the evaluation of different ML models, we find that the RF is the optimal model for neurological aspects. As a result, by taking into account the physical, mental, and social aspects and applying the best knowledge gleaned from the data, this model can help the gerontologist evaluate neurological aspects situations in older adults more quickly and present the best option for improving quality of life.

Abbreviations

- NA = Neurological Aspects
- QoL = Quality of life
- AB= Adaptive - Boost
- RF= Random Forest
- SVM= Support Vector Machine

- ML= Machine Learning

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