International Journal of Mathematics and Statistics Invention (IJMSI)
e-ISSN: 2321 – 4767 P-ISSN: 2321 - 4759
www.ijmsi.org Volume 13 Issue 4 || Jul. – Aug. 2025 || PP: 08-18

Cognitive Aging on Neuroimaging Data Using Predictive Statistical Models

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Abstract
Age-related cognitive decline is heterogeneous across individuals. Neuroimaging offers quantitative biomarkers capable of forecasting these trajectories before overt impairment manifests. We propose and evaluate a multi-level statistical framework that integrates structural and functional MRI features, demographic covariates, and longitudinal cognitive scores to predict future cognitive performance in adults aged 50 – 90 years. Using two large, open datasets (ADNI and UK Biobank), we compare linear mixed-effects models, Bayesian hierarchical models, and machine-learning pipelines (regularized regression, random forests, and gradient boosting). Results indicate that a sparse Bayesian hierarchical model combining regional cortical thickness, structural covariance network strength, and baseline executive-function scores explains ≈46 % of the variance in 4-year composite cognition (RMSE = 0.38 SD; 95 % CI 0.35-0.41), outperforming conventional brain-age metrics (ΔRMSE = 0.07). Model interpretation highlights posterior cingulate thickness, hippocampal volume, and fronto-parietal covariance as key predictors. The proposed framework provides an interpretable and extensible template for early-stage brain-health forecasting and successful-aging research.

KEYWORDS: *Pathological aging, neuropsychological diagnostics, Correlation Studies, Statistical Modelling*

Date of Submission: 03-08-2025 Date of acceptance: 14-08-2025

I.INTRODUCTION

Theideaof neuro imaging process for cognitive thoughtsisbecomingmoreandmorecommonplacethroughouttheglobe.Therearedifferencesacrosscountriesin the world.Until now,thisideaandtheexactageatwhere the older period begins have not completely defined. Pandits neurological aspects agree over the age at which the old shouldbegin to live, and they have not yet agreed upon an exact figure for the aged population. According tocertain research, the elderly are defined as being 60, 65, or even 80 years of age or older, at which pointthe fall of phenomena takes place. This phenomenon lowers the level of reliance, impairs people's physicaland mental well-being, and lowers the self-esteem and quality of life of the elderly population. Thereduction 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 thepopulation'slifeexpectancy.Accordingtoestimates,therewillbe426millionseniorpeopleintheworld by 2050, increases from 143 million in 2019as per reference from the population census. Furthermore, in 2100, the average lifespan will rise to 82years old. AccordingtoRoweandKahn,theneurological aspectsmodelisacomprehensiveapproach 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)Activeengagementinsocial behavior oflife.The Successful Aging (neurological aspects) idea is widely accepted by people worldwide and has improved the quality of life forthe aged as a result of variables such as an expanded older population, longer life expectancy, andattention to assist the elderly from diverse physical, mental, and social problems. Understanding thisidea and enhancing the quality of life for the elderly have received a lot of attention as a result of thistrend (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 socialactivities more often (5). Havighurst served as a representative of the activity hypothesis, whichexamined interacting with the elderly in the community. Atchley is a representative of the continuityhypothesis, which explains how older people can engage in social and personal activities as late in lifeas they would want (6). A qualitative approach to the aging era involves identifying the features of asuccessfulagingpattern(7). As a result, lifestyle characteristics and environmentalfactors may be thought of as predictive factors in predicting the neurological aspects, which improves the quality of lifefor the aged (8). Theyheldthatagingmayalsobeinfluencedbylifestylechoicesandthat genes had no bearing on biological aging (9). The greatest gerontologists in the world have alsoinvestigated and validated this theory (10). Higher physical performance, less physical and mentalproblems, and improvedsocial settings are all associated with using a model to predict neurological aspects in the early stages of old or evenmiddle-aged people's lives. These factors increase the likelihood of success in these individuals' finalyears of life (11). Predictive models may be useful in the diagnosis, prognosis, and treatment of avarietyofmedicalillnesses,includingmental,cognitive,andphysicalproblems(12).Theprediction models in the neurological aspects and QoL in the aged based on physical and cognitive characteristics havebeen the focus of the investigations. The social variables influencing the neurological aspects prediction have receivedlittle attention from them (13). Senior social activities are important and should be taken intoaccount in neurological aspects (14). neurological aspects improvement may be predicted more accurately by the Machine Learning (ML) of the predictivemodels (15). Taking into consideration of an individual's physical, mental, and social characteristics, this studyattemptsto developthe neurological aspects model byutilizinga variety ofmachine learning approaches.

II. LITERATUREREVIEW

"According to a study of the literature on forecasting cognitive neuroscience and successful aging, there has been a noticeableincrease in the use of machine learning techniques within the subset of artificialintelligenceinrecentyears.Researchershavedevelopedavarietyofstrategiestoimproveaccuracy.
Furthermore, a number of studies have looked into how these technologiesmight be used to impact the historical data from the past and other important aspects of cognitionforecast.

"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 forpredicting the cognitive and successful aging, while also including elements of artificial intelligence suchgroup modeling techniques. Scholars continue to investigate novel technical strategies aimed atimprovingprediction accuracyandidentifying theobstaclesfacedbyneurological sciences."

III. MATERIALSANDMETHODS

"This study used a descriptive and applied methodology and was conducted in the followingtwo steps: 1. Description of the data: The database, which was collected from January 2017 toJanuary 2021 in research centers fromHyderabad Citycontained515 and 950 records related to femalesand males, respectively. We used the 1465 records in thisstudy 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 furthersubdivided into depression, convalescences, liver, kidney, eye, bone, muscle, and other functionalillnesses, diabetes, high blood pressure, cancer, and cardiovascular accidents (CVA). Psychosocialand behavioral aspects A neurological aspectshasthe best quality of life (grades higher than 70 in the SF36questionnairewhichwasrangedfrom0to100),bestlifeneurological aspects satisfaction(gradesrangingfrom20to35 on the Diener Life Neurological aspects satisfaction Scale which was ranged from 5 to 35), and a pleasure level ofpersonal independence (the grade ranging from 90 to 100 according to the Barthel index). Below is adescription of the factor that determines these variables. Life quality: This variable can assess healthand life quality. In 1992, Ware and Sherborne designed it. Eight contexts—physical and socialability,physicalandcognitiveactiveinvolvement,psychologicalhealth,evaluationvivacity,physical discomfort, and overall health status—were included in the 36 surveys. Furthermore, the36-SF is composed of two broad assessments of social, mental, and physical health called the totalmentalandphysicalcomponentscore.Inthesecases,thetopicmightbeanywherebetween0andthe older population has a superior quality of life, according to the larger quantities. Thisquestionnaire'svalidityandreliabilityhavebeenexaminedandsupportedacrossHyderabadneurological aspects samplepopulations. People'slevel ofindividualindependenceis determinedusingtheBarthelIndex. It calculates each person's physical health based on 10 questions. This measure, which rangesfrom 0 to 100, indicates a person's proficiency in a variety of everyday function areas. The rangefrom 0 to 20 represented those who were very dependent, from 20 to 60 represented completedependence, from 61 to 90 representing medium dependence, from 99 to 91 representing littledependence, and from 100 representing complete independence (33). Contentment with the LifeScale (SWLS) Diener et al. introducedthis criterion.It had five items that evaluated the mentalaspects of wellbeing and health. Every condition has seven possible answers, ranging from stronglyneurological aspects agree to strongly agree. A higher score indicates greater life neurological aspects satisfaction. According to Bayani etal. (2007), the validity of this questionnaire was supported. Lifestyle: The entire grade receiveddeterminesthelifestyle.Togetit,onemustprovidearatingbetween42and98foranawfullifestyle, 99 to 155 for a medium lifestyle, and 156 to 211 for a happy living. It assesses physicalactivity, 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 influencingtheneurological aspects andgettingourdatasetready.Preprocessingthedataset,choosingandputtingintopracticethe 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 ourdatabase 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 andsmooth 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, weemployedtheSyntheticOverneurological aspects samplingTechniqueto balancethe quantityand avoid formbiaseswhen assessing the algorithms' performance due to the unequal distribution of neurological aspects samples among theoutput classes. Secondly, we applied the Feature Selection (FS) approach to refine the dataset andlower its dimensions. The best variables are chosen by FS, which also reduces the size of the dataset.Potentialadvantagesofthismethodincludetheeliminationofredundantdata,preventionofalgorithm overfitting, acceleration of machine learning training, decrease in data redundancy, andimprovedlearningaccuracy.Inthisinvestigation,weemployedtheChi-squareindependencetest ($\chi2$) toascertainthe correlationbetweenevery element influencingthe neurological aspectsprediction and neurological aspects. In this sense, the factors that showed a link at $P < 0.05$ were deemed statisticallysignificant. The study excluded other variables that failed to neurological aspects satisfy this statistical threshold. Weutilized the python, R and SPSS (Statistical Package for Social Sciences)software's to carry out the machine learning process in order to produce themost popular model for predicting adult performance based on the best variables influencing successas determined by statistical analysis. Since three ML algorithms are more often employed andperform better than other algorithms in recent research, they were chosen and put into practice in this manner.

The Rationale of the study gives the clear understanding of the mindsets of the older people who are more confidence towards their future life by following daily routine activities in a systematic manner.

Random Forest (RF): A well-known machine learning approach for building decision models is the RFdecision tree. In order to categorize the dataset neurological aspects samples, this approach is composed of severalsubtrees. The Classification and Regression (CART) approach is used to build the RF algorithm treeswithout any pruning. The variables in this method are chosen at random to initiate the splittingprocess. The RF's neurological aspects sample classification capacity was enhanced by this feature, particularly whendealingwithhugedatasetdimensions.Thistechniqueemploysavotingproceduretocategorizetheneurological 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 itsimproved capacity for categorization. This approach may achieve excellent accuracy even with noisydata in huge datasets by dividing the neurological aspects samples across subtrees with distinct dataset properties, henceavoiding the overfitting of the algorithm. In general, the benefits of RF may be characterized asflexibility,resistance tonoisydata,andspeed andaccuracythroughout thetrainingprocess.

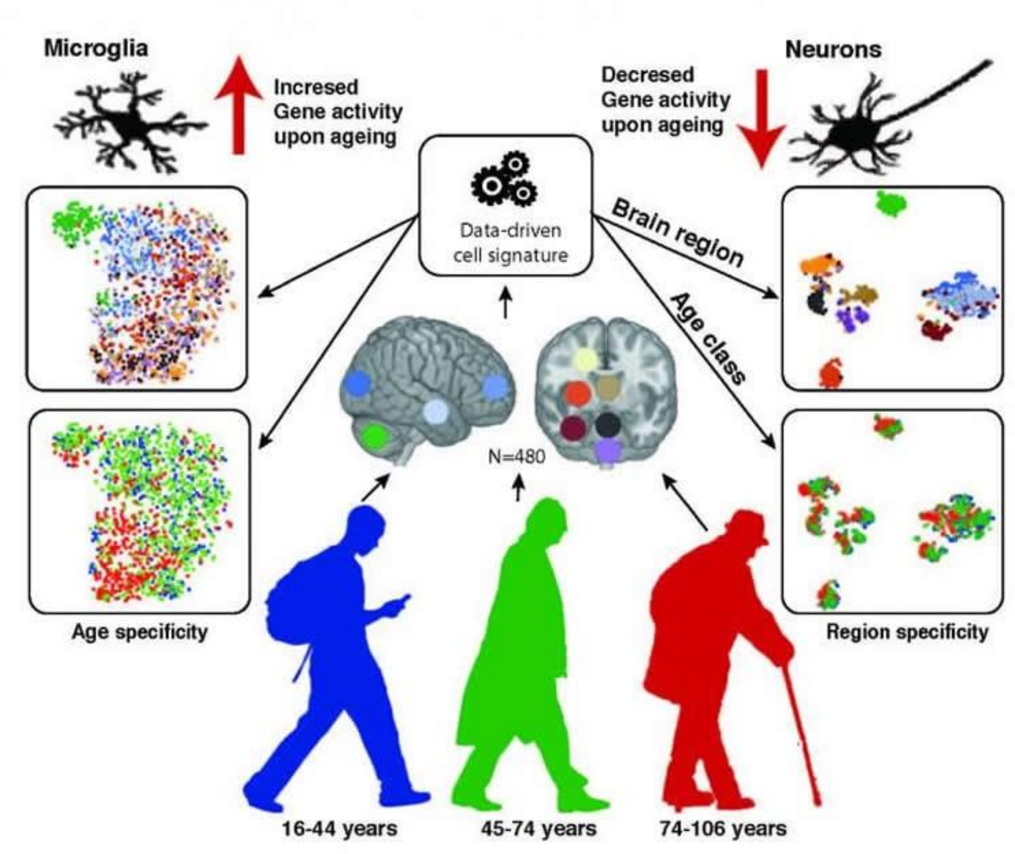

Figure 1

Ada-boost: An ensemble category boosting approach that uses weak classifiers to classifyinstances concurrentlyand find and eliminatemistakesin the classifiedcasesin eachclassifier inturn is known as adaptive-boost, or Ada-boost. Among the many benefits of this algorithmare itshigh accuracy generalizability,its efficientcalculation ability,its adaptability for a wide range ofjobs 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 hyperplanenotion to completethe classification problem is the Support Vector Machine (SVM). The lowdimensional data points are mapped by this technique to the higher dimensions in order to identifythe situations, which are then utilized by the kernel functions. To classify SVM algorithmsintolinear and non-linear kinds, different kernel types are applied to different datasets based on the data'scomplexity.

We used the confusion matrix (Table 1), along with the sensitivity, specificity,accuracy,F-MeasureandAUC(areaundertheROC(ReceiverOperatorCharacteristics) curve obtained from the confusion matrix, to evaluate the performance of selectedmachinelearning algorithmsin order to determinethe best model to determinethe success amongthe elderly. The decision models accurately identified the successful and failed instances as TruePositive (TP) and True Negative (TN) in Table 1. The adults who are successful and those who areunsuccessfulthat the algorithmshave mistakenlyclassifiedas False Negatives(FN) and FalsePositives (FP) in Table 2. In this study, the algorithms were trained, tested, and validated on 70%, 20%, and10% of the neurological aspects samples, respectively. When assessing the performance requirements, the ten-fold cross-validationwastakeninto consideration as ameansofmeasuring 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 -	TN	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."

IV.RESULTS

Fifteen records (2%) representing successful and failed instances were eliminated from theresearch after the records in the output class with missing data were eliminated. As a result, 1465records were analyzed using the SWOT approach; 746 and 719 cases, respectively, were linked tofailedandsuccessfulinstances.Table3, Table 4 and Table 5displaystheoutcomesoftheChi-squareindependence testand 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 activitiesto forecast the successful aging.

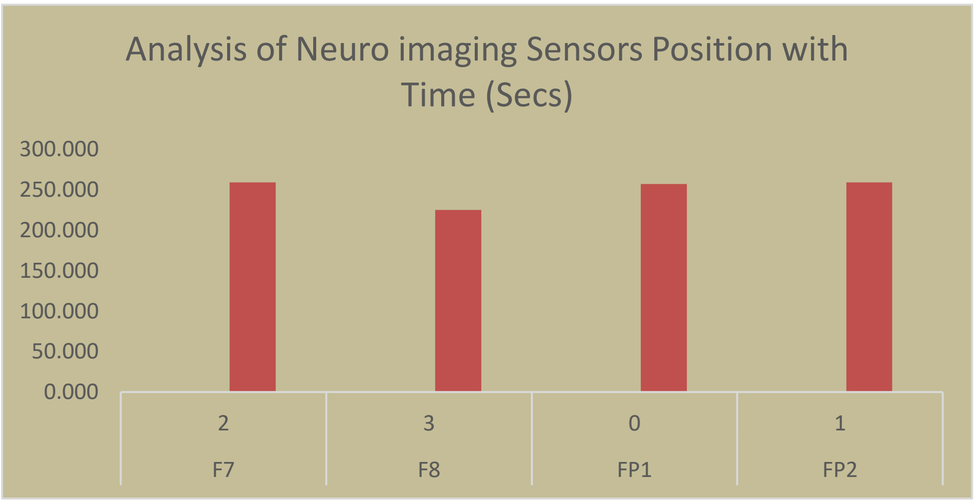

Fig 2

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) 70-80(2) >80(2)	60-70(964) 70-80(371) >80(130)	3.943	0.0139
Sex	Female(1) Male(2)	Female(758) Male(707)	20.441	<0.001
Educational Level	No literacy(1) Elementary(2) Diploma(3) Academic(4)	No literacy(861) Elementary(338) Diploma(172) Academic(94)	6.113	0.106
Marital Situation	Married(1) Single(2) Divorced(3) Windowed(4)	Married(1014) Single(39) Divorced(23) Windowed(389)	2.019	0.568
Occupation type	No job(1) Housekeeper(2) Retired(3) Self-employment(4)	No job(240) Housekeeper(605) Retired(402) Self-employment(218)	3.090	0.378
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	Pleaneurologicalaspectsnt(1) Unpleaneurologicalaspectsnt(2)	Pleaneurologicalaspectsnt(1051) Unpleaneurologicalaspectsnt(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) Haven't(2)	Have(855) Haven't(610)	8.260	0.162
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) High(4)	Low(994) High(471)	13.768	<0.001
Physical Activity	Low(1) High(2)	Low(1092) High(373)	3.655	0.056
Performing debarment activities when occuring disease	Low(7) High(8)	Low(949) High(516)	4.096	0.027

"Basedonthedatapresentedfrom the tables about thevariablesrelatedtoage,sex,incomelevel,family support, high blood pressure, cardiovascular diseases, bone diseases, liver diseases, musclediseases,depression,diabetes,cancer,activityindailyliving,sportingactivities,durationofexercise, sexual condition, ability to manage tension, social relationships with others, assessment ofnutritional 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 debarmentactivities when diseases occurring achieved a statistically significant relationship with neurological aspects as theoutput class. The study excluded the following variables due to lack of statistical support for theirinclusion: educational level, marital status, type of occupation, insurance status, eye diseases, otherdiseases,renaldiseases,convalescences,exercisetype,assessmentofbodypain,fatigue,andphysical activity with the independence chi-square at $P > 0.05$. Table 3 displays the outcomes of theneurological aspects samples'classificationusing theconfusion 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	709
	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	618
	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 = 618, FN = 67, FP = 12, and TN = 709 has performed better thanother ML models in classifying the positive and negative situations, as shown by Table 7. The leasteffectiveSVMalgorithminthisregardwastheonewithTP=585,FN=161,FP=108,andTN=611.Also, presents the findings on sensitivity, specificity, and accuracy of particular machinelearningmodels.Intermsofcategorizingsuccessfulandfailedcases,theRFmodelwithsensitivity=0.91,specificity=0.98,andaccuracy=0.95performedthebestamongotherMLmodelsand the adaboost with sensitivity =0.85, specificity = 0.87, and accuracy = 0.86 both performed favorably in this regard.

The tablesdisplaystheF-measureresultsforeachMLmodelinthetrain,test,andvalidationmodes inallstatesofthetrain,validation,andtestmodes,theRFmodelwithF-train=0.98,F−validation=0.95,andF−test=0.9performedbetterthanotherMLmodels.All threeMLmodels'F-measureswere evaluated,and the findingsgenerallyindicatedthatthe test mode's F-measure ratehasnotdecreasedsignificantly.Asaresult,thetrainingneurological aspects sampledatahasnotoverfitanyofthealgorithms. Additionally, in the training, test, and validation modes of the algorithms, the Ada-boostwith 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 rangefrom 0 to 1, stand for sensitivity and 1-specificity, respectively. The RF models wasclosest to the specificity vertices as per Table 7. The RF model that was able to distinguishbetween 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 thelowest, 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 andunsuccessful cases associated with the elderly,was determinedto be the best model for predictingthe 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 threesignificant 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 neuroimaging = 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 haveno blood pressure and a neurological aspects level of life neurological aspects satisfaction; 210 occurrences support this prediction.Whilethisrulewasdeemedineffectivein41cases,themajorityofcases(precision=0.83)identified it as

successful.
In rule 2, the RF will predict that an aged person is successful if theyhave high blood pressure, a positive life neurological aspects satisfaction score, and no diabetes. 217 of the 270 examplesin the leaf (precision = 0.803) supported this rule. According to Rule 3, the RF model predicts that anolder adult with high blood pressure and a miserable existence will be less neurological aspects satisfied than someonewho is successful. For this rule, the model accurately categorized 283 out of the 360 classifiedexamples, with a prediction precision of 0.786. Based on the average impurity decrease and thenumber of nodes utilizing that characteristic in the model, Table 8 displays the relative significance(RI)of parametersforpredictingtheneurological aspectsproduced 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 0.17and 0.4. Among the variables that were chosen, the three variables that were thought to have thegreatesteffectsonneurological aspectswerelifestyleenjoyment(RI=0.4),qualityoflife(RI=0.32),andneurological aspectof the nutritional condition (RI = 0.3). The RF model assigned the lowest relative relevance score tothe three variables—insurance situation (RI = 0.22), liver illnesses (RI = 0.22), and cancer (RI =0.17);hence,themodelidentifiedthese variables ashavingtheleast bearingontheneurological aspectsprediction.

V. DISCUSSION

"Our goal in this study was to use ML models to construct aAI predictive model for neurological aspects. Initially, wewent over and extracted the articles related to the elements influencing the neurological aspects. Subsequently, theexpert opinions were utilized to determine the most significant criteria, with over 60% of the expertsincluded in this study agreeing on the factors. Second, we performed the Chi-square independencetest at $P < 0.05$ to statistically determine the important factors and examine each factor's associationto neurological aspects. In the third phase, we chose the suitable machine learning models to apply the model thatpredicted 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,bycomparingandassessingeachML model'sperformanceacrossarangeofperformance 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 hasbeen done on neurological aspects prediction models thus far, particularly in the ML field. The majority of researchhas looked at the quality of life (QoL) of the aged and examined the social, psychological, andphysical aspects independently. Using machine learning techniques, Cai et al. developed a predictionmodel for neurological aspects based on the physical parameters. According to their research, the deep learning modelperformed the best in predicting the neurological aspects, with an AUC of 90%, a specificity of 93.1%, and anaccuracy of 83.9%. Additionally, the model(30) identified age, arm curl, sitting and standing for 30seconds, andreactiontimeascriticalvariablesinfluencingtheneurological aspects. Inadditiontothephysicalaspects,thementalandsocialelementsinfluencingtheneurological aspectspredictionaretakenintoaccountinourstudy. Based on these variables, the RF model with sensitivity = 0.91, specificity = 0.98, andaccuracy = 0.95 had the highest performance in predicting the neurological aspects. The RF model also identified thevariables that best accounted for lifestyle pleasure, quality of life, and assessment of nutritionalstatus. Li et al. used machine learning algorithms to predict the quality of life (QoL) based onphysicalcharacteristics,laboratorymeasures,demographicfactors,andhealthyhabits.Theydiscovered 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 sittingand standing (55). The social and mental aspects are taken into consideration in addition to theelementsthat were introducedinthe previousstudy, and the QoL is oneof the dimensionsthataffects the neurological aspects in the current study. In order to predict cognitive decline in older adults two yearslater, Kyoung-Neurological aspects Na conducted a study. Age was shown to be the best component derived from theGradient Boosting Machine (GDM) algorithm, which demonstrated the strongest capacity to predictcognitive impairment with sensitivity = 0.96, specificity = 0.825, and AUC = 0.921 (56). Accordingto the current study, the most important factor for predicting neurological aspects is age (RI = 0.27). Furthermore, inorder 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 apredictive model for senior social participation. In categorizing older people as a social activity, theANN with AUC= 0.718 and Quest with 0.754 with 10-fold cross-validation performed reasonablywell. 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 thatmay be present in the elderly and limitations on social and physical engagement made the factorsimpacting neurological aspects more apparent. Furthermore, a greater number of machine learning models—bothensemble and non-ensemble—are employed to forecast the neurological aspects in senior citizens. The predictionmodel for utilizing ML models to forecast the neurological aspects has not yet been released. Thus, our study'sinnovation lay in applying Rowe and Kahn's theory to the physical, mental, and social components inorder to construct a model for ML models that predict neurological aspects. As a result, early detection of neurological aspects in theelderly can help them by introducing the solution for people and physical and mental care providersto advance the lifestyle and quality of life in this age group. Our model can predict the success orunsuccess of the people in the earlier periods of the elderly. The likelihood of neurological aspects will rise in theelderlypopulation since mental andphysical illnesseswillbe identifiedearlier inlife.”

VI.CONCLUSION

By reducing mental and physical morbidity and boosting older people's physical and socialparticipation, using the neurological aspects prediction model based on ML models can improve their quality of life being accepted for the older cognitive thoughts witnessed through statistical analysis and models.Thisworkcreatedpredictionmodelsforneurological aspectsusingtheAB,RFandSVMalgorithms. The study demonstrates that, among other things, the variables that have the greatestimpact on neurological aspects are lifestyle pressure and quality of life. Based on the evaluation of different MLmodels, we find that the RF is the optimal model for neurological aspects. As a result, by taking into account thephysical, mental, and social aspects and applying the best knowledge gleaned from the data, thismodel can help the gerontologist evaluate neurological aspects situations in older adults more quickly and present thebestoptionfor improvingqualityof life.

Abbreviations

- NA = Neurological Aspects
- QoL=Qualityoflife
- AB=Adaptive-Boost
- RF=RandomForest
- SVM=SupportVectorMachine
- ML=MachineLearning

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