2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS) | 979-8-3503-0345-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/AICERA/ICIS59538.2023.10420159

Predicting the Risks of Brain Stroke Using Machine Learning Models and Artificial Neural Network

1st Nafiz Nahid
Department of Computer Science and Engineering
Sylhet Engineering College
Sylhet, Bangladesh
nafiz234.nn@gmail.com

2nd Mehrab Hossain
Department of Computer Science and Engineering
Sylhet Engineering College
Sylhet, Bangladesh
hmehrab786@gmail.com

3rd Ariful Islam Rifat
Department of Computer Science and Engineering
American International University
Dhaka, Bangladesh
aarifulrifat548@gmail.com

4th Meher Durdana Khan Raisa
Department of Software Engineering
Daffodil International University
Dhaka, Bangladesh
meher35-2818@diu.edu.bd

5th Ashraful Islam
Department of Computer Science
University of Regina
Regina, Canada
aiy497@uregina.ca

***Abstract*— The primary cause of death and disability worldwide is stroke. Accurate prediction models and identification of stroke risk factors can aid in early intervention and preventive measures. In this study, an approach based on machine learning algorithms, including Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), AdaBoost (AdB), Gradient Boosting (GB), Decision Tree (DT), and a unique Artificial Neural Network (ANN) model, is proposed to predict stroke risk at four different levels. To address the issue of imbalanced dataset, Synthetic Minority Over-sampling Technique coupled with Edited Nearest Neighbors (SMOTEENN) was used. 11 features were selected for training the models out of the initial 12 features, and the data-set was divided into an 80-20 train-test ratio for model assessment. The Decision Tree (DT) model achieved an accuracy of 98.53%. Additionally, a 1000 epoch Artificial Neural Network (ANN) model with various batch sizes was created; 128 produced the best results. Stochastic Gradient Descent (SGD), Adam, and RMSprop were examined along with other optimizers, however SGD produced the highest accuracy rate of 99.21%. The results suggest that utilizing the selected features and the balanced data-set, machine learning algorithms such as the unique CNN model can accurately predict stroke risk at various levels. These models have the potential to aid in early detection of stroke risk and guide preventive interventions, thus improving patient care and outcomes. Further testing and implementation of these models in real clinical settings are warranted.**

Keywords—Machine learning, Brain Stroke, Decision Tree, SMOTEENN, ANN

I. INTRODUCTION

A stroke, often referred to as a transient ischemic attack or a cerebrovascular accident, occurs when blood supply to the brain is compromised. As a result, the blood is unable to provide the brain with nutrition and oxygen. Brain cells deteriorate in minutes in the absence of oxygen and nutrition [1]Over the course of their lives, one in four adults over the age of 25 will experience a stroke. 12.2 million people will experience their first stroke this year, and 6.5 million of them will pass away. Stroke has afflicted almost 110 million people globally. Despite the notion that the risk of stroke significantly increases with age, 16 percent of strokes happen in those under 50, and 60 percent happen in people under 70 [2]. In the United States, stroke ranks as the sixth most prevalent cause of death. Heart disease, stroke, and other cardiovascular illnesses are currently the most common and costly health challenges confronting developed nations, with yearly healthcare and related expenses totaling around US$ 320 billion[3].The Mymensingh division in Bangladesh had the highest rate of stroke prevalence, which was 11.39 per 1000 people. The frequency was much greater in the community of older men. Ischemic strokes accounted for more than three-quarters [4].

There exist multiple risk factors for stroke, such as elevated blood pressure 65.8 percent, smoking 43 percent, diabetes mellitus 41.3 percent, underlying cardiac conditions 29.1 percent, a family history of stroke or transient ischemic attack 26.7 percent, high cholesterol 25.5 percent, a history of prior TIA 24.9 percent, and significant extracranial carotid atherosclerosis 18.18 percent. In contrast to western reporting series, the study's participants had higher rates of diabetes mellitus and lower rates of underlying heart illnesses [5].Strokes are classified into two types: ischemic and hemorrhagic. Hemorrhagic stroke is a less common type that happens when a blood artery bursts in the brain and starts to bleed into surrounding tissues. This causes pressure to build up in the surrounding brain tissue, causing further damage and discomfort. Conversely, an ischemic stroke occurs when a blood clot or plaque, which is a buildup of cholesterol and fatty deposits, obstructs a major blood vessel in the brain [6].

Early risk factor identification for illnesses like stroke is decisive for successful preventive medicine. Artificial intelligence (AI) has gained traction in medical applications such as image analysis, physiological signals, and personal medical history in recent years. In some fields of medicine, artificial intelligence (AI) may eventually take the place of human judgement by helping medical professionals make better clinical decisions. AI has the potential to transform healthcare by providing early illness identification and treatment. So, in this study we used several machine learning models to predict the likelihood of stroke and specially apply an ANN custom made model on a publicly available data-set. we hope it will help the patients and doctors to prevent an unexpected outcome.

A. Objective

The aim of this research is to create and assess the efficacy of many machine learning models and a modified artificial neural network (ANN) for the purpose of predicting an indi-

979-8-3503-0345-2/23/$31.00 ©2023 IEEE

vidual's risk of stroke. The study intends to accomplish the following goals:

- Create and train a variety of machine learning models, such as AdaBoost, SVM, K-Neighbors, Gradient Boosted, and Decision Tree, to predict the likelihood of stroke based on a collection of specified risk variables.
- Create a unique ANN model to predict the chance of stroke, exploiting deep learning algorithms' capabilities to enhance accuracy and dependability.
- To determine which model best predicts the risk of stroke, Determine the accuracy, sensitivity, specificity, precision, and area under the receiver operating characteristic (ROC) curve for each model. Review each model's performance using these metrics.
- Based on the machine learning models, determine the main factors that predict the Risks of Brain Stroke and look into the biological pathways and underlying mechanisms that may provide an explanation for these factors.
- Teach medical staff how to use the clinical aid system powered by machine learning, how to evaluate its results, and how to apply them to their clinical work.
- Providing medical personnel with a dependable and ac- curate tool to estimate the risks of brain stroke and guide treatment options would ultimately enhance patient outcomes and the quality of care received.

II. LITERATURE REVIEW

The study focuses on strokes and their effects on the central nervous system, with ischemic and hemorrhagic strokes being the most common forms. The study suggests using machine learning approaches to predict and categorize strokes based on medical data. The present research's limitations in predicting stroke risk factors. As a remedy to this restriction, the suggested Stroke Prediction (SPN) method employing an improved random forest is presented. The study emphasizes the suggested model's enhanced accuracy (96.97%) when compared to current models. The research, however, lacks comparison how the suggested model compares to other ma- chine learning techniques for stroke prediction [7].

This paper looks at how artificial neural networks (ANNs) can predict stroke based on patient physiological data. The abstract addresses the key worry in training the ANN model, which is the difference in method and the amount of hidden nodes. Each ANN architecture is run 1,000 times and 10,000 epochs throughout the study, which takes into account eight architectures and two learning strategies. The simulation results show that both the SCG and LM algorithms can obtain an averaged classification accuracy rate of more than 98 percent when 1000-fold cross-validation is used [8].

The study's goal was to predict stroke outcomes using artificial neural networks (ANN) and support vector machine (SVM) models. The study examined data from 297 people, 130 of whom were sick and 167 of whom were well, as well as 9 predictors. The features were chosen using the Cramer's V test. The study used SVM with an RBF kernel and MLP ANN for prediction based on predetermined predictors. While SVM had an accuracy of 80.38 percent and ANN had an accuracy of 81.82 percent in the training data-set, ANN had an accuracy of 85.9 percent and SVM had an accuracy of 84.62 percent in the testing data-set. The study indicated that the ANN model outperformed the SVM model in predicting stroke and would be beneficial in making clinical judgments about stroke [9].

This study uses the Cardiovascular Health Study (CHS) data-set to examine the predictive power of five machine learning algorithms for stroke. A decision tree using the C4.5 algorithm, dimension reduction with Principal Component Analysis (PCA), artificial neural networks (ANN), and support vector machines (SVM) for classification are some of the methods employed. The study examines numerous data samples and concludes a composite approach of DT, PCA, and ANN produces the best results for stroke prediction. The research contributes to the literature on stroke prediction using machine learning approaches and emphasizes the need of integrating various methods for reliable predictions [10].

This research provides a noninvasive method for detecting strokes early. It focuses on anticipating strokes utilizing time series-based algorithms like as FFNN, LSTM, GRU, and biLSTM based on processed EEG data. All of the algorithms perform well in the experiments, with GRU attaining the greatest accuracy of 95.6%. The discoveries might help doctors diagnose strokes earlier and save lives. The study emphasizes the need for inexpensive and noninvasive technologies for early stroke diagnosis, as existing procedures based on MRI and CT scans are costly. The study contributes to the body of knowledge by looking at the use of EEG data for stroke diagnosis and analyzing the efficacy of numerous time series- based algorithms [11].

III. METHODOLOGY

There are three sections in this section: description of the data, evaluation matrices and classifiers for machine learning, and implementation techniques. These are the three procedures :

A. Data Description

In this paper, Data-Set is collected from [7] Machine Learning Repository which contains 4900 entries and 12 attributes. It has both categorical features also numerical features. At- tributes are described below:

1. *Age:* Patient ages are from 1 to 90 years and the average age 50 years.
2. *Gender:* Male represented as 0 and woman as 1. The vast majority of patients are male.
3. *NHISS:* It's known as the National Institutes of Health Stroke Scale which has 46 unique categories.
4. *mrs:* Magnetic Resonance Spectroscopy is used to study the metabolic changes in brain tumors, stroke, and different situations of diseases. This category has eight distinct values.
5. *systolic:* Systolic point value of the blood pressure.
6. diastolic: The blood pressure's diastolic point value.
7. *Glucose:* The patient's blood glucose level.
8. *Paralysis:* Is the sufferer paralyzed in any way?

9. *Smoking:* It relates to the patient's smoking history and categorizes it into three categories.
10. *Bmi:* The patient's BMI (body mass index).
11. *Cholesterol:* The average cholesterol level in both changes is about the same, ranging between 215 and 220.
12. *TOS:* Thoracic outlet syndrome refers to three related disorders that include nerve, artery, and vein compression in the lower neck and upper chest area (TOS).
13. *risk:* It is the target feature of this problem which has 4 categories meaning 4 different risk type of the patient.

B. Machine Learning Classifier

Machine learning classification models [12] are algorithms that learn from labeled data to make predictions about new, unlabeled data. In our research, we use seven different models to encounter the problem. Model descriptions are given below:

1) Decision Trees: The most effective and widely used categorization and prediction technique is the decision tree. A decision tree is a type of tree structure that looks like a flowchart, where each leaf node (terminal node) carries a class label, each internal node represents a test on an attribute, and each branch indicates a test outcome.

2) Logistic Regression: This statistical model, often known as a logit model, is frequently applied to predictive analytics and classification tasks. The likelihood of an event happening is calculated using logistic regression using a collection of independent variables, such voting or not.

3) K-Nearest Neighbors (KNN): The k-nearest neighbours technique, also referred to as KNN or k-NN, is a supervised learning classifier that is non-parametric that forecasts data point grouping based on closeness. Predictions are made by this non-parametric model using the k closest data points in the training set. The model's accuracy is determined by the value of k.

4) Gradient Boosting: Another machine learning approach involves combining many weak models, usually decision trees, to create a powerful model. Gradient boosting builds trees one after the other, trying to fix the flaws of the preceding tree, in contrast to random forests.

5) Support Vector Machines (SVMs): SVMs are a kind of supervised learning technique that can be applied to problems involving regression or classification. The primary goal of support vector machines (SVMs) is to identify the hyperplane that best divides the various classes in the training set. The hyperplane with the largest margin—that is, the distance between the hyperplane and the closest data points from each class is found in order to accomplish this.

6) AdaBoost: This is another supervised learning approach that brings together several weak models to create a strong model. It builds trees progressively, like gradient boosting, except it gives greater weight to miss-classified samples with each iteration.

7) Artificial Neural Network: This paper, developed a custom classification model by the artificial neural network. The model uses a combination of 2 categorical features and 9 continuous feature classes. There are two dense layers in the model architecture, each with 200 and 115 neurons. The model also incorporated embedding layers to handle the categorical features, with shapes of (2, 1) and (4, 2), respectively. During the training model, used a binary cross entropy loss function and different optimizers that also included dropout regularization to prevent over-fitting, with a rate of 0.5 for the first layer and 0.4 for the second layer.

C. Evaluation Matrics

Models are used for different works the same as ours and their performance is evaluated by confusion matrix, accuracy precision, recall, and f-1 score [13].

1. *Classification Accuracy:* It can be calculated by dividing the total number of input samples by the number of accurate predictions shown in "Equation (*1*)".

$$Accuracy = \frac{number\ of\ correct\ prediction}{total\ number\ of\ prediction} \qquad (1)$$

2. *Confusion Matrix:* It produces a matrix [14] that de-scribes the overall performance of the model as an output where
TP = True Positive
FP = False Positive
FN = False Negative
TN = True Negative
By averaging the numbers along the principal diagonal, one may determine the accuracy of the matrix as shown in "Equation (*2*)".

$$Accuracy = \frac{TP + FP}{N} \qquad (2)$$

where N is the number of samples.

3. *F1:* It is applied in order to evaluate the test's validity. The F1 Score is calculated using the Harmonic Mean of memory and accuracy. There are two possible F1 Scores: 0 and 1. It is an indicator of your classifier's accuracy and resilience. It is represented mathematically as "Equation (*3*)"

$$F1 = 2 * \frac{1}{\frac{1}{precision} + \frac{1}{recall}} \qquad (3)$$

F1 Score attempts to strike a compromise between precision and recall.

4. *Precision:* The computation involves splitting the quantity of favourable results that the classifier in "Equation (*4*)" has predicted. by how many

successful outcomes the classifier predicted displayed:

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

5. *Recall:* It is computed by dividing the entire number of pertinent samples by the quantity of legitimately positive outcomes. It is represented mathematically as "Equation (*5*)":

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

D. Implementation Procedures

In this part, the research present the steps to address the issue. The Scikit-learn and Python libraries were used. The subsequent steps were taken:

1) *Input Data:* The total number of participants in the Mendeley data set utilized for this research is 4,799, with 3,123 men and 1,676 females. The data set also comprises a summary of the major characteristics.

2) *Data Preprocessing:* Twelve categories are present and numerical attributes in the data set that are missing values. Before separating the variables with missing values, first normalize the data and label encode categorical data to numerical data. Two strategies were used to fill the missing values: the first included anticipating the values using machine learning techniques, and the second involved statistical analysis, such as calculating the median or average of the qualities. We used statistical methods for numerical continuous values and decision trees for categorical variables. Before to making a specific prediction, we remove the missing variables. After splitting the train-test data, we fit the decision tree model. The data-set is now prepared for additional analysis.

3) *Feature Engineering:* The target feature is called Risk, and it is categorized into "0", "1", "2", "3".

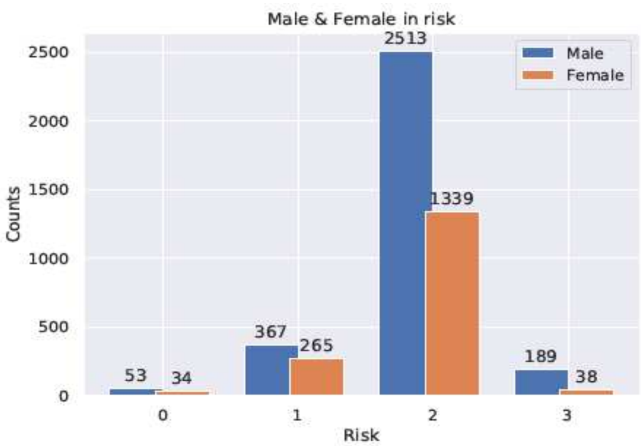

Fig. 1. Risk by gender

If the risk is "0" the patient is at Low risk. If the risk is "1" the patient is at Moderate risk. If the risk is "2" the patient is at High risk.

Finally, if the risk is "3" the patient is at "Severe risk. Thus, 53 males and 34 females have a value of "0", while 367 male and 265 female have a value of "1", and 2513 male and 1339 female have a value of "2", the remaining 189 male and 38 female have a value of "3" shown in "Fig. 1". To correct this imbalance, we applied the SMOTEENN [15] approach, often known as synthetic minority oversampling technology. Following that, the data-set size increased to 14668.

4) *Feature Selection:* the study employed a mix of the Chi-Square test and the Correlation Coefficient technique to improve our model's performance toward the goal answer. In statistics, the autonomy of two occurrences is evaluated using the chi-square test. The observed count O and the expected count E can be obtained using the data of two variables. Chi-Square computes the variance between anticipated and observed counts.

High correlation characteristics, on the other hand, are more linearly dependent and hence have about the same impact as the dependent variable. When two features have such a high correlation, one of them might be dropped. Following that, we select 2 category features and 9 continuous features to train our models, for a total of 11 features.

5) *Split Data:* dividing the data set [16] in half, allocating 80% of the set for testing and 20% for training, respectively, as determined by the train test split from sci-kit learn, with 2934 items in test and the remaining 11734 in training.

6) *Basis Algorithm:* To train and test the suggested technique, seven algorithms are used as the basis algorithm. These algorithms were chosen in order to offer a variety of techniques and methods, enabling a thorough assessment of the suggested method.

7) *Model Optimization:* Models are optimized through parameter adjustments. Each model's confusion matrix is measured in order to calculate its accuracy, recall, f-1 score, FP rate, and FN rate.

8) *Best-Model:* The accuracy of the six algorithms is tested on a data-set in this technique to generate the accuracy of various kinds of algorithms and discover the optimum model.

E. Workflow Diagram

The workflow diagram from the "Fig. 2" describes our full end-to-end working procedure graphically. This visual aid makes our operational procedures easy to grasp and communicate in a smooth manner by providing a clear, step-by-step description. This diagram is a useful tool that helps our work more efficiently overall, collaborate better, and optimize our work processes.

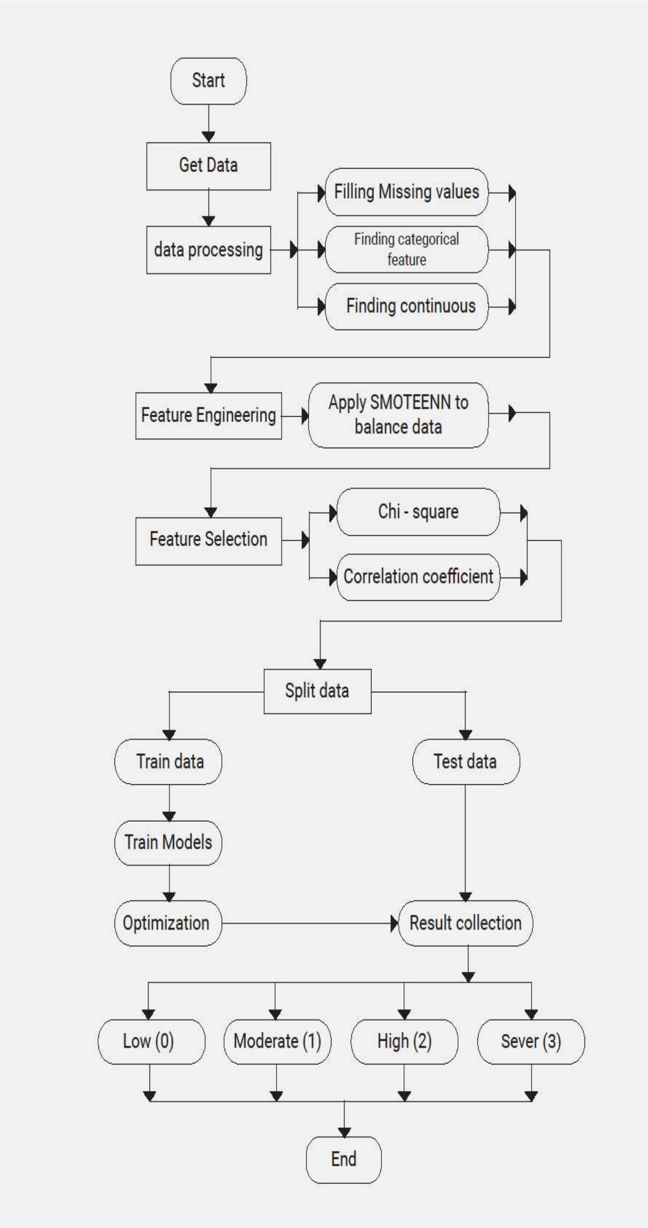

Fig. 2. Workflow Diagram

IV. Result and Discussion

A. Feature Selection Result

We utilized the Chi-Square test and the Correlation Coefficient to choose the features.

1. *Categorical Features:* Gender, Smoking Status.
2. *Continuous Features:* NIHSS, mrs, systolic, diastolic, glucose, paralysis, age, bmi, cholesterol, TOS.

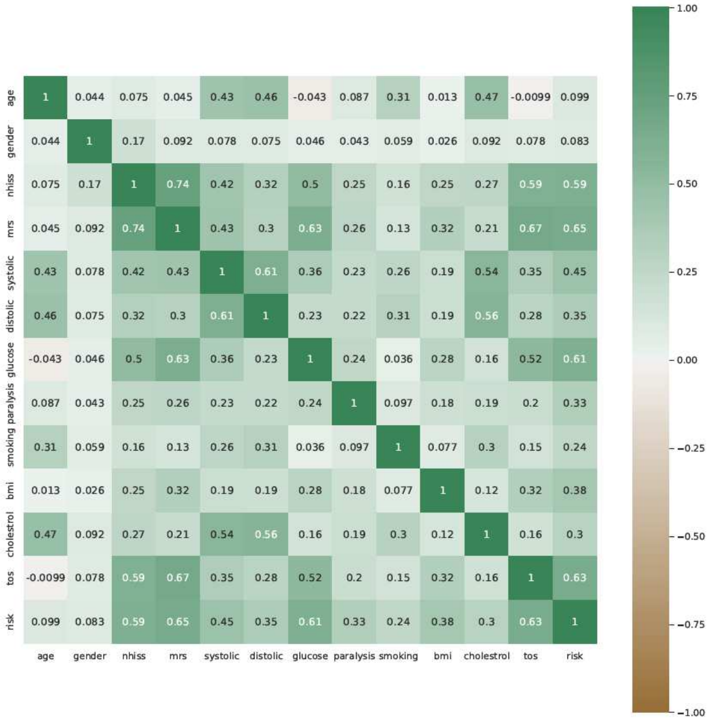

Fig. 3. Correlation Heat-map between selected features

The correlation heat-map is shown in “Fig. 3” we saw that continuous features are more positively correlated with target features and categorical values are more negatively correlated.

B. Identify the Headings

We obtained the following accuracy numbers after applying several Machine Learning Algorithms to the data-set.

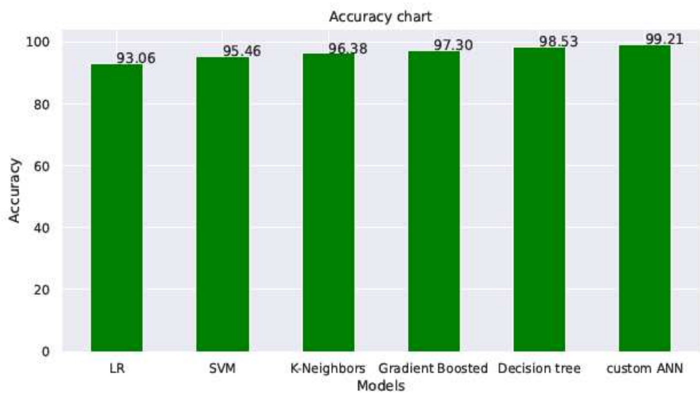

Fig. 4. Accuracy Comparison

The maximum accuracy is 99.21% for custom ANN model “Fig. 4”. Then the accuracy is 98.53% for ”Decision Tree” which is 0.68% less. The lowest accuracy is 93.06% from Logistic Regression, after than ”support Vector Machines” has 95.46%, ”K-Nearest Neighbors” has 96.38% and ”XGboost” has 97.30% accuracy, but ”Adaboost” has too much low accuracy to mention. The precision , recall and f1-scores are around same as accuracy for all the models.

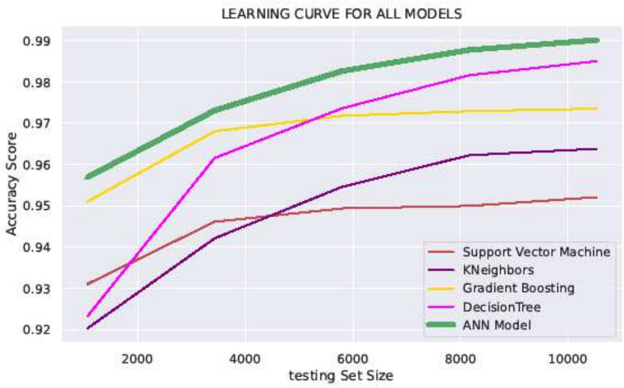

Fig. 5. Learning curve

Text From the Learning curve shown in “Fig. 5” the Decision Tree model has a low start then lastly got a good accuracy. But the ANN model has a good start and the final accuracy is highest than the other models.

TABLE 1. ANN MODEL WITH DIFFERENT OPTIMIZER

Optimizer	Batch size	Precision	Recall	Accuracy
Adam	16	95.40	95.56	95.42
	32	96.07	95.12	95.75
	64	96.72	96.29	96.72
	128	96.92	95.73	96.48
RMSprop	16	95.87	95.59	95.83
	32	96.08	95.69	95.87
	64	96.44	96.55	96.92
	128	97.63	96.10	97.18
SGD	16	97.37	97.44	97.50
	32	97.69	97.57	97.84
	64	98.72	97.21	98.53
	128	99.53	99.18	99.21

Figure In the ANN model 3 optimizer 4 different batch were used shown in “Table 1”. The Stochastic gradient descent(SGD) optimizer and 128 batch size with 1000 epoch has the best the result among others. Here in the first 380 epochs, the learning rate was 0.01, then till 640 epochs, the learning rate was 0.001 and after that the learning rate was 0.001. The learning rate was used in such a manner to avoid overfitting and underfitting problems.

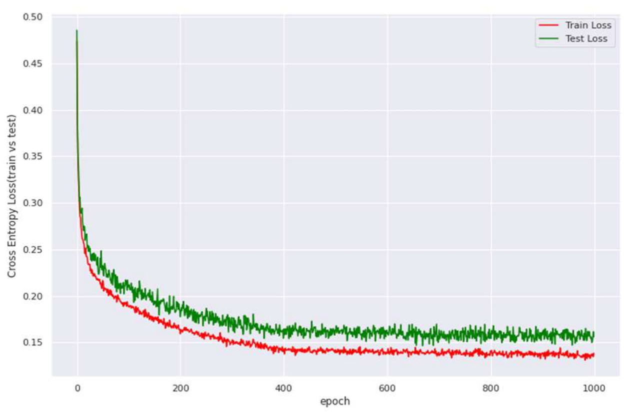

Fig. 6. Entropy loss

The In “Fig. 6” the loss is decreasing in a good way. Here Stochastic gradient descent optimizer and 128 batch size with 1000 epoch are used.

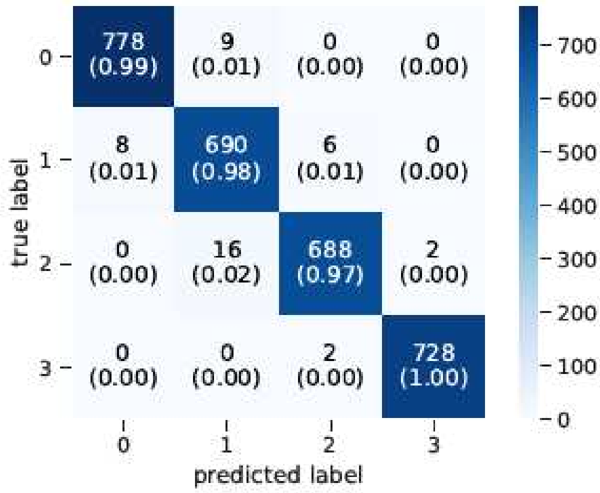

Fig. 7. Confusion Matrix Decision Tree

The “Fig. 7” shows the confusion matrix of the Decision Tree machine leaning model where risk0 has 99% accuracy, risk1 has 98% accuracy, risk2 has 97% accuracy and risk3 has 100% accuracy.

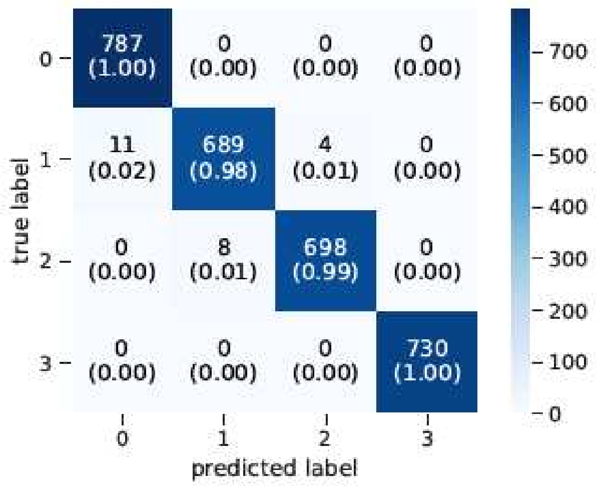

Fig. 8. Confusion Matrix Decision Tree

From the confusion matrix shown in “Fig. 8”, the ANN model has not predicted the risk1 and risk2 successfully but predicted accurately risk0 and risk3 (100%) . So, it shows the difference between this two models and the ANN model has better result.

V. CONCLUSION

This study investigated the use of some machine learning classifier models, including an Artificial Neural Network model (ANN), to estimate the probability of having a brain stroke. The findings showed that the ANN model performed better than other classifier methods, predicting stroke risks with an amazing accuracy of 99.21%. The excellent accuracy of the ANN model shows that it has the potential to be an effective tool for identifying those who are at risk of stroke and assisting in the prevention of this important medical disease. The results of this study have important ramifications for the future design of a ”Django” based online platform that may offer stroke risk prediction based on data provided by the user. By using such a platform, both individuals and healthcare professionals may be able to assess a person’s risk of stroke and take necessary precautions.

Overall, the results of this study demonstrate the potential of the machine learning methods, particularly ANN models, to identify the brain stroke risk factors. The creation of a web platform for risk prediction using ”Django” might have a big impact on increasing early identification and prevention of stroke, which would eventually improve health outcomes for people who are at risk.

References

[1] “Stroke - What Is a Stroke? | NHLBI, NIH.” Accessed: Mar. 27, 2023. [Online]. Available: https://www.nhlbi.nih.gov/health/stroke

[2] “Learn about stroke | World Stroke Organization.” Accessed: Mar. 27, 2023. [Online]. Available: https://www.world-stroke.org/world-stroke-day-campaign/why-stroke-matters/learn-about-stroke

[3] “The Healthy People 2020 website has been archived.” Accessed: Mar. 27, 2023. [Online]. Available: https://www.healthypeople.gov/2020/topics-objectives/topic/heart-disease-and-stroke

[4] M. B. A. Mondal, A. T. M. H. Hasan, N. Khan, and Q. D. Mohammad, “Prevalence and risk factors of stroke in Bangladesh: A nationwide population-based survey,” eNeurologicalSci, vol. 28, p. 100414, Sep. 2022, doi: 10.1016/J.ENSCI.2022.100414.

[5] S. N. Khan, E. Ahmed Vohra, N. Nazimabad, K. -Pakistan, S. N. Khan H-, and M. Arcade, “Risk factors for stroke: A hospital based study,” Citeseer, vol. 23, no. 1, pp. 17–22, 2007, Accessed: Mar. 27, 2023. [Online]. Available: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=89779b19881b85af7eff6f39322bad2a5a2c9cb2

[6] “Risk Factors for Stroke | Johns Hopkins Medicine.” Accessed: Mar. 27, 2023. [Online]. Available: https://www.hopkinsmedicine.org/health/conditions-and-diseases/stroke/risk-factors-for-stroke

[7] V. Bandi, D. Bhattacharyya, and D. Midhunchakkravarthy, “Prediction of brain stroke severity using machine learning,” Revue d’Intelligence Artificielle, vol. 34, no. 6, pp. 753–761, Dec. 2020, doi: 10.18280/RIA.340609.

[8] C. Peng, S. Wang, S. Liu, … Y. Y.-2020 I. 2nd, and undefined 2020, “Artificial neural network application to the stroke prediction,” ieeexplore.ieee.org, Accessed: Mar. 27, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9203638/

[9] C. Colak, E. Karaman, M. T.-C. methods and programs in, and undefined 2015, “Application of knowledge discovery process on the prediction of stroke,” Elsevier, Accessed: Mar. 27, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169260715000565

[10] M. S. Singh, P. Choudhary, and K. Thongam, “A comparative analysis for various stroke prediction techniques,” Communications in Computer and Information Science, vol. 1148 CCIS, pp. 98–106, 2020, doi: 10.1007/978-981-15-4018-9_9.

[11] M. Kaur, S. R. Sakhare, K. Wanjale, and F. Akter, “Early Stroke Prediction Methods for Prevention of Strokes,” Behavioural Neurology, vol. 2022, 2022, doi: 10.1155/2022/7725597.

[12] B. M.-I. J. of S. and R. (IJSR) and undefined 2020, “Machine learning algorithms-a review,” researchgate.net, 2018, doi: 10.21275/ART20203995.

[13] T. Ornob, G. Roy, E. H.-I. in M. Unlocked, and undefined 2023, “CovidExpert: A Triplet Siamese Neural Network framework for the detection of COVID-19,” Elsevier, Accessed: Nov. 05, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352914822002933

[14] J. T. Townsend, “Theoretical analysis of an alphabetic confusion matrix,” researchgate.net, vol. 9, no. 1, pp. 40–50, Jan. 1971, doi: 10.3758/BF03213026.

[15] V. Kumar, G. Lalotra, P. Sasikala, D. Rajput, R. K.- Healthcare, and undefined 2022, “Addressing binary classification over class imbalanced clinical datasets using computationally intelligent techniques,” mdpi.com, Accessed: Nov. 05, 2023. [Online]. Available: https://www.mdpi.com/2227-9032/10/7/1293

[16] “Stroke_Analysis - Mendeley Data.” Accessed: Apr. 10, 2023. [Online]. Available: https://data.mendeley.com/datasets/jpb5tds9f6