IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 3, September 2024, pp. 3010~3017
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i3.pp3010-3017

Enhancing stroke prediction using the waikato environment for knowledge analysis

Muneera Altayeb, Areen Arabiat
Department of Communications and Computer Engineering, Faculty of Engineering, Al-Ahliyya Amman University, Al-Salt, Jordan

Article Info

Article history:

Received Jan 5, 2024
Revised Feb 13, 2024
Accepted Feb 28, 2024

Keywords:

Multi-layer perceptron
Naive Bayes
Random forest
Support vector machine
Waikato environment for knowledge analysis data mining

ABSTRACT

State-of-the-art data mining tools incorporate advanced machine learning (ML) and artificial intelligence (AI) models, and it is widely used in classification, association rules, clustering, prediction, and sequential models. Data mining is important for the process of diagnosing and predicting diseases in the early stages, and this contributes greatly to the development of the health services sector. This study utilized classification to predict the stroke of a sample of the patient dataset that was taken from Kaggle. The classification model was created using the data mining program waikato environment for knowledge analysis (WEKA). This data mining tool helped identify individuals most at risk of stroke based on analysis of features extracted from the patient’s dataset. These features were used in classification processes according to the naive Bayes (NB), random forest (RF), support vector machine (SVM), and multi-layer perceptron (MLP) algorithms. Analysis of the classification results of the previous algorithms showed that the SVM outperformed other algorithms in terms of accuracy (94.4%), sensitivity (100%), and F-measure (97.1%). However, the NB algorithm had the best performance in terms of precision (95.7%).

Corresponding Author:

Muneera Altayeb
Department of Communications and Computer Engineering, Faculty of Engineering
Al-Ahliyya Amman University
Al-Saro, Al-Salt, Amman, Jordan
Email: m.altayeb@ammanu.edu.jo

1. INTRODUCTION

Stroke, a potentially fatal consequence of atrial fibrillation, poses challenges in its prediction for doctors due to its time-consuming and tedious nature. It primarily affects individuals over the age of 65 and is comparable to a "heart attack" in its damaging effect on the brain. In the United States and agricultural nations, stroke is the third leading cause of death. It occurs when the brain's blood supply is obstructed or reduced. There are two main types of stroke: ischemic stroke, caused by insufficient blood flow, and hemorrhagic stroke, caused by bleeding. Hemorrhagic stroke can be further classified into subarachnoid hemorrhage and intracerebral hemorrhage [1]. Stroke ranks among the world's main causes of mortality and disability. Stroke ranks second in Korea in terms of causes of death. The population of Korea is expected to age quickly; by 2050, the proportion of people over 60 is expected to rise from 13.7% in 2015 to 28.6% [2]–[4].

Islam *et al*. [5] introduced adaptive gradient boosting machine learning (ML) models to classify and predict acute stroke in active states. The study was conducted on electroencephalogram (EEG) of 75 healthy adults without a history of any neurological diseases, and 48 patients who had been diagnosed with an acute stroke. Results showed that the proposed model was approximately 80% accurate in classifying the stroke group. In a study on stroke prediction, researchers explored the use of three ML models: deep neural network

(DNN), random forest (RF), and logistic regression (LR). They evaluated the models' performance with specific parameters and found that DNN, commonly used for predicting ischemic or acute stroke, showed promise for long-term prediction as well. The DNN model achieved an impressive 88% accuracy when considering input variables, outperforming the other models. The researchers highlighted the need to enhance the model with automated and precise calculations, reducing the dependence on simpler models [6].

Hadianfard *et al.* [7] presented a study that aimed to predict stroke patients' survival rates by extracting decision rules through the use of data mining techniques. The researchers used the multiple imputation method to handle missing data when analyzing data from 4149 stroke patients that they had obtained from paper medical records. To balance the target variable, they used methods like under- and oversampling in addition to synthetic minority oversampling (SMOTE). Stroke patients' survival rate was predicted using the LR, decision tree, and SVM algorithms. The repeated incremental pruning to produce error reduction (RIPPER) algorithm was also used to extract decision rules. In terms of kappa (33.34), sensitivity (79.06%), and accuracy (76.96%), LR outperformed the other algorithms. Nonetheless, the specificity (65.35%) and area under the ROC curve (AUC) (0.77) were lower than other algorithms. Using an independent dataset of 234 records, the LR algorithm that performed the best on the primary dataset was tested. When this method was used with the external validation dataset, its accuracy (79.91%), sensitivity (83.94%), kappa (39.26), and AUC (0.8) all improved; its specificity (60.98%) did not change.

Choi *et al.* [8] created a new methodology for applying deep learning models to raw EEG data that does not take frequency features into account. Using real-time EEG sensor data, the proposed stroke prediction model was developed and trained. Several deep learning models specializing in time series data classification, and prediction long short term memory (LSTM), bidirectional LSTM, convolution neural network (CNN)-LSTM, and CNN-bidirectional LSTM were created and compared. When using raw EEG data, the LSTM bidirectional CNN model predicted stroke with 94.0% accuracy and low false positive rate (6.0%) and false negative rate (5.7%), demonstrating high confidence in our method.

Modern ML algorithms and data preprocessing tools are arranged in an orderly manner on the waikato environment for knowledge analysis (WEKA) workbench. Using these methods from the command line is the primary method of interacting with them. However, easy-to-use interactive graphical user interfaces are available for data exploration, large-scale experiment setups on distributed computing platforms, and stream data processing configuration design. These interfaces make up a sophisticated setting for data mining experiments. The GNU general public license governs the distribution of the Java-written system [9].

The novelty of this work lies in the use of a huge dataset to train several ML classifiers supported by the WEKA data mining tool for stroke prediction. The prediction process in the proposed model is divided into four stages; i) choosing the data set, ii) dataset cleaning and preprocessing, iii) classification using four algorithms naive Bayes (NB), RF, support vector machine (SVM), and multi-layer perceptron (MLP), and iv) results and performance evaluation. The performance of the classifier is evaluated using the following metrics: accuracy, sensitivity, precision, and F-measure.

2. PROPOSED METHOD

The proposed model aims to detect stroke using ML and deep learning classifiers embedded in the data mining tool WEKA, which allows users to categorize accuracy using various algorithmic methods, based on a set of features [10]–[12]. Before starting the classification process, the dataset is first filtered and pre-processed to become ready as features that can be fed to classifiers, as this is the first and most important step in the process of developing a ML classifier. In the next step, the dataset is divided into test datasets and training datasets and to gauge and analyze the performance, the cross-validation method is used in our model proposed in this paper, 10 folds are used; the test is conducted on each fold independently, while the other nine folds are used to learn. The 1/10 dataset that is retained separately is used to compute the error rate [13], [14]. The classification process is then carried out based on four algorithms NB, RF, SVM, and MLP. Figure 1 describes the model proposed in this work.

2.1. Dataset

The dataset used in this study was obtained from Kaggle [15], where it consists of 3254 cases, each containing eight attributes: age, gender, heart disease, hypertension, marital status, average blood sugar level, body mass index, and smoking. These attributes are initialized by filtering them in a preprocessing or cleaning step that involves deleting rows that include redundant, corrupted, incomplete, inaccurate, or incorrectly structured data from a dataset. Then datasets are converted to the comma separated value (CSV) file format, which is a compatible format with WEKA. Table 1 shows the attributes and description of the dataset used in the classification process.

– Gender: a person's gender is indicated by this characteristic. 2,117 men (41.4%) and 2,994 women (58.6%) comprise the male and female population. Disproportionately afflict women, with sociocultural gender playing a role in variations in risk factors, evaluation, treatment, and results. The study focuses on the gaps in existing knowledge and research [16].

- Age: this feature describes an individual's age, as the occurrence of strokes in young individuals rises as they age beyond 35 years, and there has been a 23% increase in such cases over ten years, primarily due to a rise in ischemic stroke [17].
- Hypertension: this feature determines if the individual has hypertension, a condition that impacts 9.8% of the participants and raises the risk [18].
- Heart disease: this feature signifies the presence or absence of heart disease in the individual. The percentage of patients diagnosed with heart disease stands at 5.4% [19].
- Ever married: this feature displays the participants' marital status, with married individuals making up 65.6% of the sample [20].
- Average glucose level: this feature captures the participant’s average glucose level [21].
- BMI: this feature records the participants' body mass index [22].
- Smoking: three categories are included in this feature, which tracks the participant's smoking status: formerly smoking (21.2%), never smoking (40.9%), and smoking (37-8%) [23].

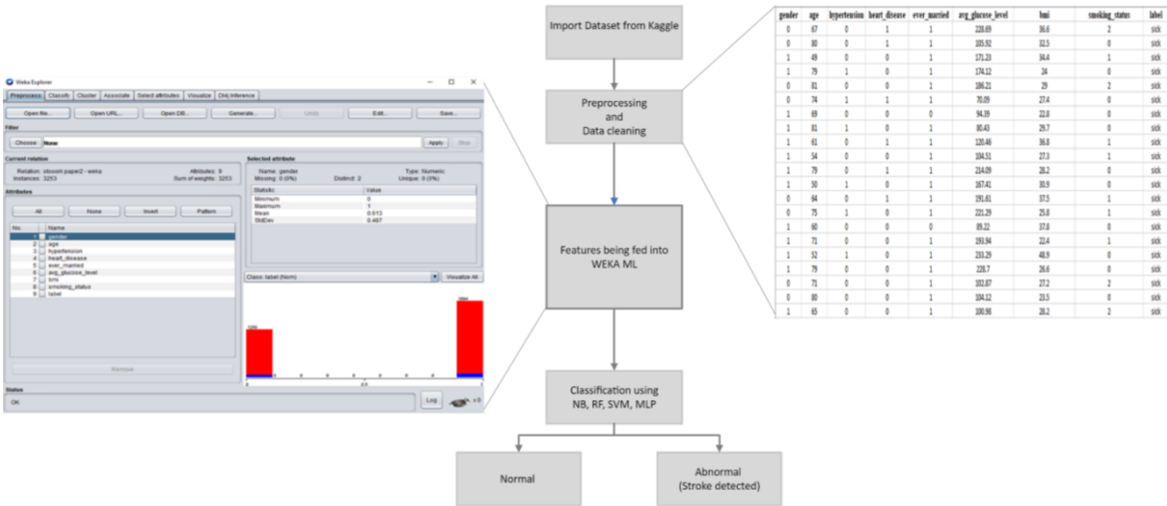

Figure 1. Architecture phases of the proposed model

Table 1. Attributes and data description [15]

Variable	Classification	Data type	Frequency	Percentage (%)
Gender	Male	Nominal	1260	38.7
	Female		1994	61.3
Age	>35	Nominal	2484	76.3
	<=35		770	23.7
Hypertension	Yes	Nominal	408	12.5
	No		2846	87.5
Heart disease	Yes	Nominal	205	6.3
	No		3049	93.7
Ever married	Yes	Nominal	2598	79.8
	No		656	20.2
Average glucose level	>120	Nominal	759	23.3
	<=120		2495	76.7
BMI	>=25	Nominal	2557	78.6
	<25		697	21.4
Smoking	Formerly smoking	Nominal	814	25.0
	Smokes		728	22.4
	Never smoke		1712	52.6

2.2. Machine learning classifiers

ML is the scientific study of algorithms and statistical models used by computer systems to execute tasks without explicit programming which has quickly improved in recent years in the context of data analysis and computing, allowing applications to work intelligently. Applications like web search engines, data mining, image processing, and predictive analytics are commonplace and use these methods. Because algorithms learn automatically, this is the main advantage [24], [25]. In this research, several classifiers were tested and compared for stroke detection and will be discussed in the following subsection.

2.2.1. Naive Bayes classifier

One of the most widely used data mining methods is the NB algorithm. Its efficiency assumes attribute independence, which may be broken in many real-world data sets. Several attempts have been made to reduce the assumption, with attribute selection being one major technique. It calculates the possibility that a new sample belongs to a particular class based on the argument that all features are independent of each other given the class [26], [27]. Given the prior probabilities, P(c), P(x), and P(x|c), one may calculate the posterior probability, P(c|x), using the Bayes theorem. The NB classifier assumes that the influence of a predictor's (x) value on a given class (c) is independent of the values of the other predictors. In (1) illustrates this assumption, which is known as class conditional independence [28].

$$\mathrm{P}(\mathrm{x}|\mathrm{c}) = \frac{\mathrm{P(xlc)P(c)}}{\mathrm{P(x)}}$$
$$\mathrm{P}(\mathrm{x}|\mathrm{c}) = \mathrm{P}(\mathrm{x}, \mathrm{lc})\ \mathrm{xP}(\mathrm{x2}|\mathrm{c})\mathrm{x}..\times \mathrm{P}(\mathrm{x}, |\mathrm{c}) \times\ \mathrm{P}(\mathrm{c}) \tag{1}$$

2.2.2. Random forest classifiers

An algorithm uses a bagging algorithm to group data, obtain decision tree models, and combine sub-small models for a final model. The prediction results are based on voting, with the largest vote-based classification [29]. One of the ensemble learning strategies that belongs to the homogeneous base learner group in terms of constructive classifiers is reinforcement learning (RF). The first type is computational, while the second is statistical. From a computational standpoint, the RF has the potential to cope with both regression and classification problems [30].

2.2.3. Support vector machine

The optimal hyperplane that is closest to every data point is the target of the SVM training. In order to decrease the overall separation between each data point and the hyperplane plane, the hyperplane parameters are continually adjusted during the training phase [31]. SVM uses structural risk minimization to solve a limited quadratic optimization problem to segregate data across a decision boundary, often known as the hyperplane f(x)=0. The items in the provided data input x_i (i = 1, 2, …, N) have labels that differ and correspond to the positive and negative classes. Yields the hyperplane dividing the provided data in the case of linearly distributed data, as shown in (2):

$$y = F(x) = W^T x + b = \sum_{i=1}^{N} W_i x_i + b \tag{2}$$

The vector W and scalar b determine the best-separating hyperplane, which maximizes the distance between the plane and the closest data. Using the kernel function, SVM may be applied to non-linear classification tasks when the features in high-dimensional feature spaces are non-linearly separable [32].

2.2.4. Multi-layer perceptron

MLP is a kind of neural network that employs the back-propagation method for supervised learning. MLP architecture is composed of a three-layer configuration: input layer, hidden layer(s), and output layer(s); in which every neuron is connected to every other neuron in the layer above it. MLP is said to perform exceptionally well in non-linear issues regularly [33]. Figure 2 demonstrates the MLP neural networks' architecture.

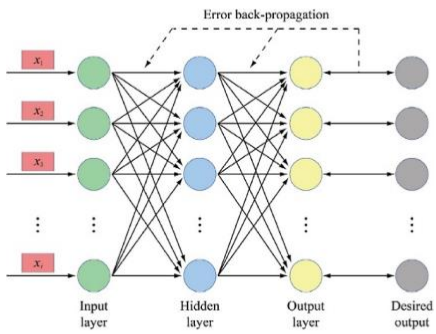

Figure 2. MLP neural networks' architecture [34]

3. PERFORMANCE EVALUATION AND CLASSIFICATION RESULTS

In this paper, the classification process was implemented using multiple classifiers NB, RF, SVM, and MLP for stroke detection on the registered dataset. The performance of the proposed model was evaluated using different metrics, the first of which is the accuracy measure, as it has been used in many studies to determine the classification accuracy according to in (3) [35]. One of the measures also used in this paper is precision which is a measure of data accuracy achieved when limited information is available. In binary classification, precision can be equated to positive predictive values. The subsequent statement represents the rule for determining precision. As demonstrated by (4) [36].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{4}$$

On the other hand, to measure the amount of total positive samples (TP+FN) that were assigned to positive categories (TP), the sensitivity measurement index was used. In other words, the ratio of true positives to the total ratio of actual yeses appears in (5) [37]. The F-measure was also used in this work by calculating the harmonic mean of precision and sensitivity by assigning equal weight to each of them. In (6) shows the F-measure [38].

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{5}$$

$$\text{F} - \text{Measure} = \frac{2 * \text{Precision} * \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{6}$$

3.1. Confusion matrix

The confusion matrix is an important metric for assessing the accuracy of models. Furthermore, the confusion matrix concept is perplexing [39]. Table 2 shows the confusion matrix for a binary classifier where the predicted values are denoted as positive (1) and negative (0), while the actual values are marked true (1) and false (0). Classification model possibilities are estimated from the expressions TP, TN, FP, and FN found in the confusion matrix [40], [41].

In this paper, four different classification processes were performed and the performance of each was evaluated based on the result of the confusion matrix as shown in Tables 3 to 6. From these results, we note that NB achieved an accuracy of 90.4% while the accuracy of the MLP and RF classifiers reached 94.0%. Finally, SVM excels with accuracy, reaching 94.4%.

Table 2. Confusion matrix [42]

		Predicted	
		Congested	Uncongested
Actual	Congested	True positive (TP)	False negative (FN)
	Uncongested	False positive (FP)	True negative (TN)

Table 3. Confusion matrix for NB

Confusion Matrix	Normal	Sick
Normal	2891	182
Sick	129	51

Table 4. Confusion matrix for RF

Confusion matrix	Normal	Sick
Normal	3058	15
Sick	180	0

Table 5. Confusion matrix for SVM

Confusion matrix	Normal	Sick
Normal	3037	0
Sick	180	0

Table 6. Confusion matrix for MLP

Confusion matrix	Normal	Sick
Normal	3051	22
Sick	174	6

On the other hand, when we compare these classification results, as in Table 7 and Figure 3, we can notice that the NB has the highest precision score of 95.7%. In terms of sensitivity and F-measure, SVM also has the highest results of 100% and 97.1%, respectively. According to these results, the superiority of SVM over other classifiers appears, with an accuracy of 94.4% and 100% for sensitivity, and it performed well regarding precision with 94.4% and 97.1% for F1 score. On the other hand, the accuracy demonstrated in this paper is shown to be superior to previous research. As in Islam *et al.* [5] the accuracy rate was 80%; in Heo *et al.* [6], the accuracy rate was 88%; and in Hadianfard *et al.* [7], the accuracy rate was 76.96%. However, in this study, the accuracy rate was around 94.4%.

Table 7. Performance comparison of classifiers (10-fold cross-validation)

Classifier	NB (%)	RF (%)	SVM (%)	MLP (%)
Accuracy	90.400	94.0	94.4	94.0
Precision	95.7	94.4	94.4	94.6
Sensitivity	94.1	99.5	100	99.3
F-measure	94.9	96.9	97.1	96.9

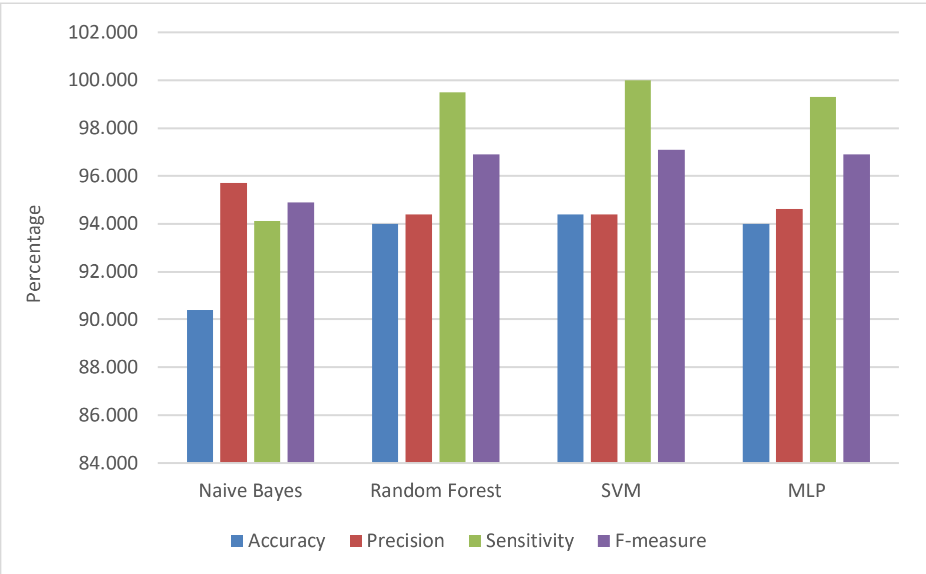

Figure 3. Performance comparison of classifiers (10-fold cross-validation)

4. CONCLUSION

To complete our study, we had to evaluate several classification algorithms to detect stroke based on a set of features such as age, hypertension, heart disease, blood sugar, BMI, marital status, and smoking status. WEKA data mining software was used to evaluate and analyze the NB, RF, SVM, and MLP algorithms. Regarding classification performance metrics, the performance was measured by performing a variety of evaluation metrics, such as accuracy, precision, sensitivity, and F-measure on stroke datasets using 10-fold cross-validation, SVM demonstrated strong generalization ability, achieving reliable results on both training and testing datasets, with values of 94.4%, 100%, and 97.1% for accuracy, sensitivity, and F-measure, respectively. In future work, a combination of other classification methods may be used to enhance the results.

REFERENCES

[1] H. K. V, H. P, G. Gupta, V. P, and P. K B, “Stroke prediction using machine learning algorithms,” *International Journal of Innovative Research in Engineering & Management*, vol. 8, no. 4, Jul. 2021, doi: 10.21276/ijirem.2021.8.4.2.
[2] D. Pastore *et al.*, “Sex-genetic interaction in the risk for cerebrovascular disease,” *Current Medicinal Chemistry*, vol. 24, no. 24,

Sep. 2017, doi: 10.2174/0929867324666170417100318.
[3] H. C. Kim, D. P. Choi, S. V. Ahn, C. M. Nam, and I. Suh, “Six-year survival and causes of death among stroke patients in Korea,” *Neuroepidemiology*, vol. 32, no. 2, pp. 94–100, Nov. 2009, doi: 10.1159/000177034.
[4] H. Lee, S. H. Oh, H. Cho, H. J. Cho, and H. Y. Kang, “Prevalence and socio-economic burden of heart failure in an aging society of South Korea,” *BMC Cardiovascular Disorders*, vol. 16, no. 1, Nov. 2016, doi: 10.1186/s12872-016-0404-2.
[5] M. S. Islam, I. Hussain, M. M. Rahman, S. J. Park, and M. A. Hossain, “Explainable artificial intelligence model for stroke prediction using EEG signal,” *Sensors*, vol. 22, no. 24, 2022, doi: 10.3390/s22249859.
[6] J. N. Heo, J. G. Yoon, H. Park, Y. D. Kim, H. S. Nam, and J. H. Heo, “Machine learning-based model for prediction of outcomes in acute stroke,” *Stroke*, vol. 50, no. 5, pp. 1263–1265, 2019, doi: 10.1161/STROKEAHA.118.024293.
[7] Z. Hadianfard, H. L. Afshar, S. Nazarbaghi, B. Rahimi, and T. Timpka, “Predicting mortality in patients with stroke using data mining techniques,” *Acta Informatica Pragensia*, vol. 11, no. 1, pp. 36–47, 2022, doi: 10.18267/j.aip.163.
[8] Y. A. Choi *et al.*, “Deep learning-based stroke disease prediction system using real-time bio signals,” *Sensors*, vol. 21, no. 13, 2021, doi: 10.3390/s21134269.
[9] E. Frank *et al.*, “WEKA-a machine learning workbench for data mining,” in *Data Mining and Knowledge Discovery Handbook*, Springer US, 2009, pp. 1269–1277, doi: 10.1007/978-0-387-09823-4_66.
[10] G. Aksu and N. Doğan, “An analysis program used in data mining: WEKA,” *Journal of Measurement and Evaluation in Education and Psychology*, vol. 10, no. 1, pp. 80–95, 2019, doi: 10.21031/epod.399832.
[11] Z. B. Zamir, “Can the WEKA data mining tool be used in developing an economic growth model?,” *Journal of Accounting, Business and Management (JABM)*, vol. 30, no. 2, Nov. 2023, doi: 10.31966/jabminternational.v30i2.919.
[12] N. Nissa, S. Jamwal, and M. Neshat, “A technical comparative heart disease prediction framework using boosting ensemble techniques,” *Computation*, vol. 12, no. 1, 2024, doi: 10.3390/computation12010015.
[13] K. A. Shakil, S. Anis, and M. Alam, “Dengue disease prediction using weka data mining tool,” *arXiv-Computer Science*, pp. 1-26, Feb. 2015, doi: 10.48550/arXiv.1502.05167.
[14] J. R. M. Navin and R. Pankaja, “Performance analysis of text classification algorithms using confusion matrix,” *International Journal of Engineering and Technical Research (IJETR)*, vol. 6, no. 4, pp. 75–78, 2013.
[15] Fedesoriano, “Stroke prediction dataset,” *Kaggle*, 2021, Accessed: Feb. 12, 2024. [Online]. Available: https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset
[16] K. M. Rexrode, T. E. Madsen, A. Y. X. Yu, C. Carcel, J. H. Lichtman, and E. C. Miller, “The impact of sex and gender on stroke,” *Circulation Research*, vol. 130, no. 4, pp. 512–528, 2022, doi: 10.1161/CIRCRESAHA.121.319915.
[17] M. S. Ekker, J. I. Verhoeven, I. Vaartjes, K. M. V. Nieuwenhuizen, C. J. M. Klijn, and F. E. D. Leeuw, “Stroke incidence in young adults according to age, subtype, sex, and time trends,” *Neurology*, vol. 92, no. 21, pp. e2444–e2454, 2019, doi: 10.1212/WNL.0000000000007533.
[18] J. Dubow and M. E. Fink, “Impact of hypertension on stroke,” *Current Atherosclerosis Reports*, vol. 13, no. 4, pp. 298–305, 2011, doi: 10.1007/s11883-011-0187-y.
[19] C. W. Tsao *et al.*, “Heart disease and stroke statistics-2022 update: a report from the american heart association,” *Circulation*, vol. 145, no. 8, pp. E153–E639, 2022, doi: 10.1161/CIR.0000000000001052.
[20] S. Ramazanu, A. Y. Loke, and V. C. L. Chiang, “Couples coping in the community after the stroke of a spouse: a scoping review,” *Nursing Open*, vol. 7, no. 2, pp. 472–482, Nov. 2020, doi: 10.1002/nop2.413.
[21] Á. Chamorro *et al.*, “Glucose modifies the effect of endovascular thrombectomy in patients with acute stroke,” *Stroke*, vol. 50, no. 3, pp. 690–696, Mar. 2019, doi: 10.1161/STROKEAHA.118.023769.
[22] F. Q. Nuttall, “Body mass index: obesity, BMI, and health: a critical review,” *Nutrition Today*, vol. 50, no. 3, pp. 117–128, 2015, doi: 10.1097/NT.0000000000000092.
[23] B. Pan, X. Jin, L. Jun, S. Qiu, Q. Zheng, and M. Pan, “The relationship between smoking and stroke a meta-analysis,” *Medicine (United States)*, vol. 98, no. 12, 2019, doi: 10.1097/MD.0000000000014872.
[24] P. Refaeilzadeh, L. Tang, and H. Liu, “On comparison of feature selection algorithms,” in *Proceedings of AAAI workshop on evaluation methods for machine learning II*, pp. 34-39, 2007.
[25] I. H. Sarker, M. H. Furhad, and R. Nowrozy, “AI-driven cybersecurity: an overview, security intelligence modeling and research directions,” *SN Computer Science*, vol. 2, no. 3, 2021, doi: 10.1007/s42979-021-00557-0.
[26] S. Chen, G. I. Webb, L. Liu, and X. Ma, “A novel selective naïve Bayes algorithm,” *Knowledge-Based Systems*, vol. 192, 2020, doi: 10.1016/j.knosys.2019.105361.
[27] S. Sayad, “Naive bayesian,” *Presentation*. Accessed: Feb. 12, 2024 [Online]. Available: https://www.saedsayad.com/naive_bayesian.htm
[28] P. Langley and S. Sage, “Induction of selective Bayesian classifiers,” in *Uncertainty Proceedings 1994*, Elsevier, 1994, pp. 399–406, doi: 10.1016/b978-1-55860-332-5.50055-9.
[29] B. Mahesh, “Machine learning algorithms-a review,” *International Journal of Science and Research (IJSR)*, vol. 9, no. 1, pp. 381–386, 2020, doi: 10.21275/ART20203995.
[30] Q. Xu and J. Yin, “Application of random forest algorithm in physical education,” *Scientific Programming*, vol. 2021, pp. 1–10, Sep. 2021, doi: 10.1155/2021/1996904.
[31] M. Savargiv, B. Masoumi, and M. R. Keyvanpour, “A new random forest algorithm based on learning automata,” *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–19, 2021, doi: 10.1155/2021/5572781.
[32] M. Wei, W. Meng, F. Dai, and W. Wu, “Application of machine learning in predicting the rate-dependent compressive strength of rocks,” *Journal of Rock Mechanics and Geotechnical Engineering*, vol. 14, no. 5, pp. 1356–1365, 2022, doi: 10.1016/j.jrmge.2022.01.008.
[33] P. F. Orrù, A. Zoccheddu, L. Sassu, C. Mattia, R. Cozza, and S. Arena, “Machine learning approach using MLP and SVM algorithms for the fault prediction of a centrifugal pump in the oil and gas industry,” *Sustainability*, vol. 12, no. 11, 2020, doi: 10.3390/su12114776.
[34] A. Pinkus, “Approximation theory of the MLP model in neural networks,” *Acta Numerica*, vol. 8, pp. 143–195, 1999, doi: 10.1017/S0962492900002919.
[35] Ž. Vujović, “Classification model evaluation metrics,” *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 6, pp. 599–606, 2021, doi: 10.14569/IJACSA.2021.0120670.
[36] A. Tharwat, “Classification assessment methods,” *Applied Computing and Informatics*, vol. 17, no. 1, pp. 168–192, 2018, doi: 10.1016/j.aci.2018.08.003.
[37] F. Rahmad, Y. Suryanto, and K. Ramli, “Performance comparison of anti-spam technology using confusion matrix classification,” *IOP Conference Series: Materials Science and Engineering*, vol. 879, no. 1, 2020, doi: 10.1088/1757-899X/879/1/012076.

[38] H. Yun, “Prediction model of algal blooms using logistic regression and confusion matrix,” *International Journal of Electrical and Computer Engineering*, vol. 11, no. 3, pp. 2407–2413, 2021, doi: 10.11591/ijece.v11i3.pp2407-2413.
[39] D. Li, F. Huang, L. Yan, Z. Cao, J. Chen, and Z. Ye, “Landslide susceptibility prediction using particle-swarm-optimized multilayer perceptron: Comparisons with multilayer-perceptron-only, BP neural network, and information value models,” *Applied Sciences*, vol. 9, no. 18, Sep. 2019, doi: 10.3390/app9183664.
[40] G. Zeng, “On the confusion matrix in credit scoring and its analytical properties,” *Communications in Statistics - Theory and Methods*, vol. 49, no. 9, pp. 2080–2093, 2020, doi: 10.1080/03610926.2019.1568485.
[41] R. AlShboul, F. Thabtah, A. J. W. Scott, and Y. Wang, “The application of intelligent data models for dementia classification,” *Applied Sciences*, vol. 13, no. 6, 2023, doi: 10.3390/app13063612.
[42] D. Fuqua and T. Razzaghi, “A cost-sensitive convolution neural network learning for control chart pattern recognition,” *Expert Systems with Applications*, vol. 150, 2020, doi: 10.1016/j.eswa.2020.113275.

BIOGRAPHIES OF AUTHORS

Muneera Altayeb obtained a bachelor’s degree in computer engineering in 2007, and a master’s degree in communications engineering from the University of Jordan in 2010. She has been working as a lecturer in the Department of Communications and Computer Engineering at Al-Ahliyya Amman University since 2015, in addition to her administrative experience as assistant dean of the Faculty of Engineering during the period (2020-2023). Her research interests focus on the following areas: digital signals and image processing, machine learning, robotics, and artificial intelligence. She can be contacted at email: m.altayeb@ammanu.edu.jo.

Areen Arabiat earned her B.Sc. in Computer Engineering in 2005 from al Balqaa Applied University, and her M.Sc. in Intelligent Transportation Systems (ITS) from Al Ahliyya Amman University in 2022. She is currently a computer lab supervisor at the Faculty of Engineering, Al-Ahliyya Amman University since 2013. Her research interests are focused on the areas: machine learning, data mining, artificial intelligence, and image processing. She can be contacted at email: a.arabiat@ammanu.edu.jo.