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ORIGINAL ARTICLE

Accurate and dynamic predictive model for better prediction in medicine and healthcare

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Abstract
Introduction Information and communication technologies (ICTs) have changed the trend into new integrated operations and methods in all fields of life. The health sector has also adopted new technologies to improve the systems and provide better services to customers. Predictive models in health care are also influenced from new technologies to predict the different disease outcomes. However, still, existing predictive models have suffered from some limitations in terms of predictive outcomes performance.
Aims and objectives In order to improve predictive model performance, this paper proposed a predictive model by classifying the disease predictions into different categories. To achieve this model performance, this paper uses traumatic brain injury (TBI) datasets. TBI is one of the serious diseases worldwide and needs more attention due to its seriousness and serious impacts on human life.
Conclusion The proposed predictive model improves the predictive performance of TBI. The TBI data set is developed and approved by neurologists to set its features. The experiment results show that the proposed model has achieved significant results including accuracy, sensitivity, and specificity.

Keywords Accuracy · Features · Outcomes · Prediction · Predictive models · Sensitivity · Specificity · Traumatic brain injury

Introduction

Information and communication technologies (ICTs) have changed the trend of operations in all fields of life such as transportation, industries, and healthcare systems [1–3]. The healthcare sector has also adopted new technologies to make their system operation more efficient. Predictive models have been used from the last decade to predict the disease outcome for future decisions. The main aim of any predictive models is to provide accurate disease outcomes [4]. The accurate prediction refers to an uncertain event to identifying new disease outcomes from previous data [5]. The disease prediction outcomes help the medical staff and doctors for future decisions [6]. Before these predictive models, medical staff and doctors predict or estimate the disease outcomes by their professional expertise and opinions based on previous experiences. With the advancement of new technologies, the previous predictive methods have changed into efficient predictive models to determine the patient disease treatment. Predictive models have a proper guideline for doctors and medical staff to select the more accurate treatment therapies for patients. Predicted and prognostic models are interchangeable with each other to provide the binary and multi-class problems. In multi-class prediction, issues are related with classification of different instances into one or more than one classes. The binary prediction issues are related with classification of instances into two classes.

Traumatic brain injury (TBI) is a serious disease and a most common cause of disability and death. There is one way and hope for improvement in early care and functional outcome by using the scientific evidence-based guidelines. TBI is graded as

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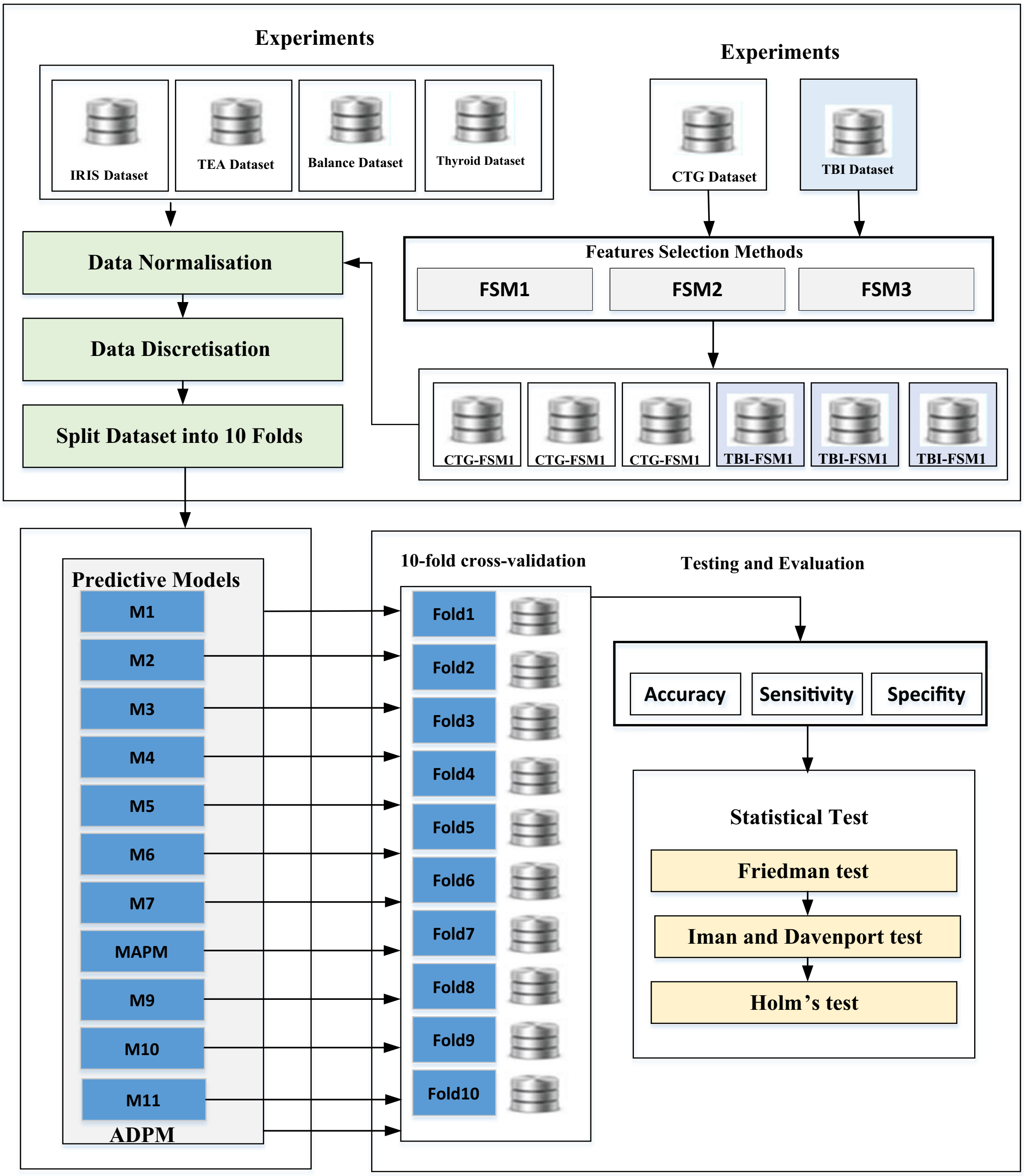

Fig. 1 Accurate and dynamic predictive model framework

moderate, severe, and mild level of consciousness. This disease is serious for skulls, which damages the brain functions, and it is also classified based on injury seriousness. TBI patients are categorized into basic five types including dead, vegetative, severe disability, moderate disability, and good recovery condition. TBI patients end up with coma, permanent disability, or death. In addition, TBI patients have severe hypotension and brain swelling issues which are not treated properly and cause brain damage and death.

Different types of predictive models have been developed for disease prediction. The existing predictive models have some limitations and drawbacks that are not well established for TBI patients. The existing predictive models have unsatisfactory results due to unavailability of multi-class prediction. Multi-class prediction is very important to enhance performance of TBI outcomes. Various existing predictive models are used for prediction and classification such as AdaBoost and support vector machine (SVM), artificial neural network (ANN), logistic regression (LR), decision tree (DT), Bayesian network (BN), and discriminant analysis (DA) [7, 8]. In addition, another issue in the TBI predictive model is affinity predictive model usage to develop and provide multi-class prediction. There is a need to develop and design new predictive models to improve predictive performance. The features

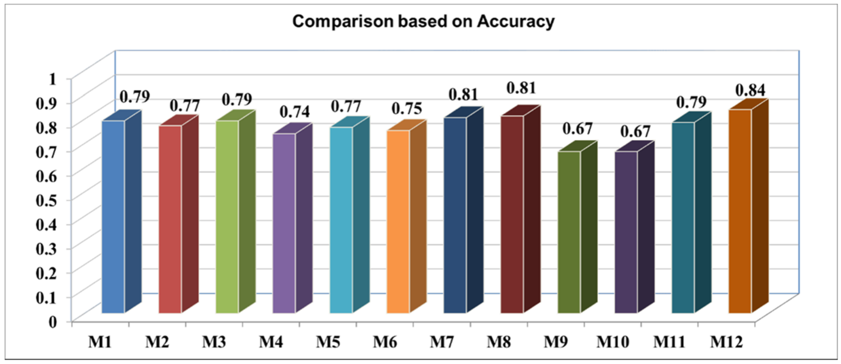

Fig. 2 Average accuracy of 10-fold cross-validation based on TBI-CMIM datasets

determined from existing TBI models need to be evaluated by neurology experts for further better results.

In order to address and improve existing predictive model performance for TBI, this paper proposes a new predictive model. The proposed model obtains a better prediction for TBI outcomes based on the Glasgow Outcome Scale. The new predictive model will be helpful for better predictive performance of existing predictive models and will be useful in the developed TBI predictive model for predicting TBI outcomes. A dynamic weighted sum multi-criteria decision-making method is proposed in this paper for multiple prediction for the accurate and dynamic predictive model (ADPM) and for obtaining a better predictive performance for prediction and classification compared to existing benchmark predictive models.

The rest of the paper is organized as follows: the "Related work" section provides related work in the field. The "Proposed accurate and dynamic predictive model" section discusses the proposed predictive model. The "Experiments and results" section presents the results. The "Conclusion" section concludes the paper with future direction.

Related work

The main aim of the predictive model is to construct a model that is capable of making the predictions [9]. Cheng et al. [10] further affirmed that predictive models are usually based on combined outcomes, which are connected with some special features. On the other hand, according to Siegel [11], the predictive models also contain machine learning methods which learn certain variables from a training dataset to predict the outcomes. The terms "predictive analytics" and "predictive model" can be used interchangeably. Recently, predictive models play a significant role in healthcare applications to predict the patient outcomes based on different features (biomarkers). In the past, physicians have relied on predictions from the provider (professional) individuals' experience and their opinion. For more accuracy, the prediction models are designed to assist doctors, physicians, and service providers. In addition, these models help to provide healthcare guidelines for different policies and also to determine the patient abilities for new treatments. These decisions and policies are helpful for selecting the suitable therapies for patients' treatment management and support systems. Various predictive models have been developed to combine the medical knowledge and help to reduce the subjectivity and increase the objectivity. Predictive models are also used to educate the medical students and physicians for accurate prognosis [12]. The prediction models are necessary for researchers and clinical practitioners in the field of medicine. Due to the widespread availability of new predictive models, it is significant for researchers and medical practitioners to select the most suitable and efficient model in order to clinically solve prediction problems.

The artificial neural network (ANN) refers to a computational model inspired by the connectivity of neurons to animate the nervous systems and is widely used as a method for classification and prediction. McCulloch and Pitts [13] developed a

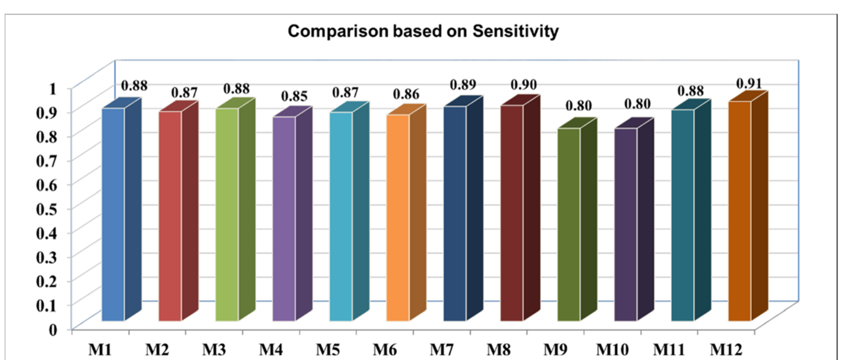

Fig. 3 Average of sensitivity of the 10-fold cross-validation based on TBI-CMIM datasets

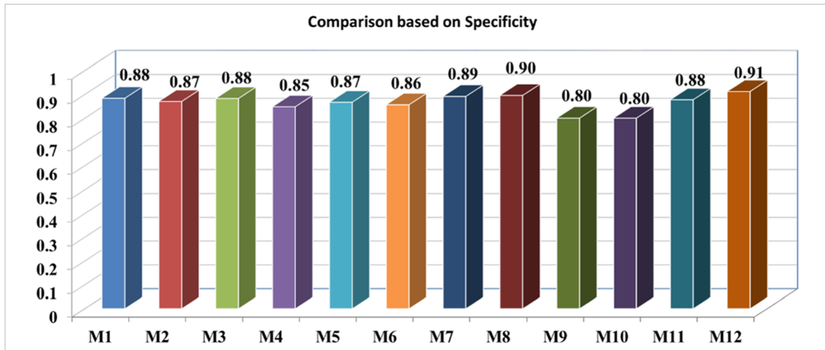

Fig. 4 Average of specificity of 10-fold cross-validation based on TBI-CMIM datasets

computational model based on threshold logic (mathematics algorithm) for neural networks. In this model, the neural network research is divided into two approaches. The first approach is used for brain biological processes, and the second one focused on the neural network application in AI (artificial intelligence). Ding et al. [14] reported that during the last 30 years, ANN has been used widely with remarkable developments. The wide acceptance and usage of ANN are because of its ability in mapping.

The ensemble predictive model is an ideal model to consider all large numbers of infinity or virtual copies of a system. Each copy represents the possible state which might be in real system. This method uses multiple learning algorithms for better predictive performance and is achieved by any constituent learning algorithms. In a statistical mechanics, the ensemble is usually infinite. The machine learning ensemble is used to concrete the finite set for alternative models. In addition, it also allows the flexibility structure to exist among those alternatives. Adaptive boosting or AdaBoost designed by Freund and Schapire in 1996 is considered as a well-known ensemble algorithm. Through an iterative process, it enhances the simple boosting algorithm [15–17].

Bayes' law or rule or theorem refers to the probability of an event related to conditions which is based on the event. Basically, by Bayes theorem', naive Bayes uses a probabilistic classifier with independent strong assumptions between the features to obtain a classification [18, 19]. In addition, it worked well in various difficult real situations because of its naive design and oversimplified assumptions. Witten and Frank [20] discussed the Bayesian classification problem where some theoretical reasons' NB classifiers behave with unreasonable efficacy. However, there is only one notable feature of NB classifiers which is a small training data to approximate the parameters which are essential for categorization. Bhargavi and Jyothi [19] reported that there is no need for the entire covariance matrix to be ascertained, and only variable variances and each class should be resulted.

The discriminant analysis (DA) model is a general form of Fisher's linear discriminant. It is usually utilized to search a linear combination of features which are separated by two or more than two events or classes of objects. The terms "LDA" (linear discriminant analysis) and "Fisher's linear discriminant" are often used interchangeably [21]. DA is a well-known classifier to solve the problems [22]. Fisher's discriminant analysis is used in a binary classification problem case and developed to solve a multi-classification problem by Johnson and Wichern [17]. McLachlan [23] highlighted that the DA linked with analysis of variance (ANOVA) and with regression analysis. DA also attempts to present a dependent variable based on measurement or linear combination of other features. However, it is different from MANOVA and ANOVA and used differently to predict one or multiple ANOVAs. It also uses continuous dependent variables through one or more independent categorical variables. It determines whether it is a set of effective variables to predict the category membership that discriminant function analysis will be useful. DA is also utilized when the groups are well known as prior (dissimilar in cluster analysis). Every case should

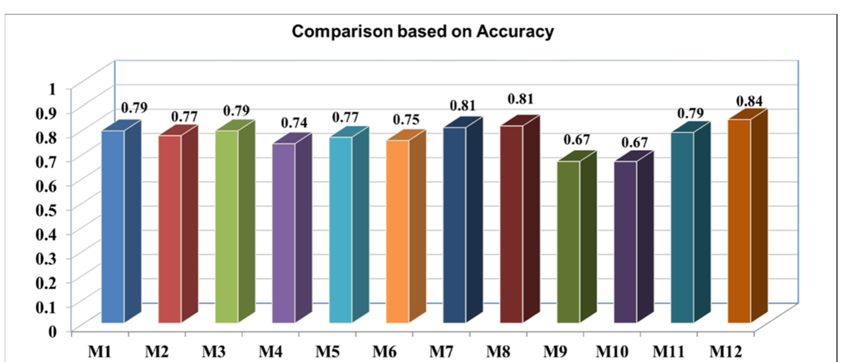

Fig. 5 Average accuracy of 10-fold cross-validation based on balance datasets

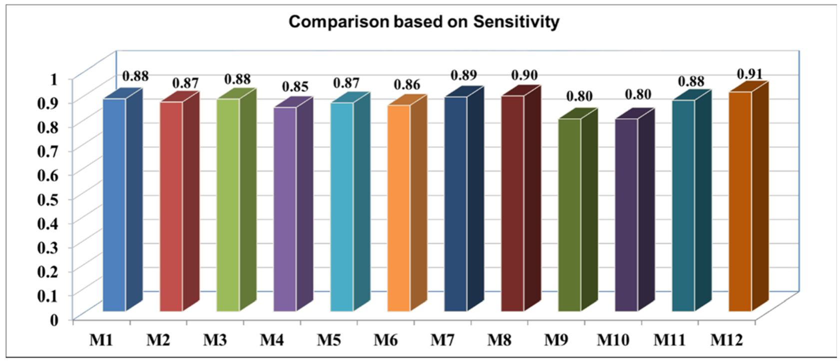

Fig. 6 Average sensitivity of the 10-fold cross-validation based on balance datasets

have a score of one or more scores on a group measure and quantitative predictor measures.

A decision tree model is used to address the classification issue by building a tree, continuously dividing the input space, where the nodes have single class points. In other words, decision trees are for presenting such mappings and consist of node attributes or tests, which are linked with decision nodes or two or more sub-trees and leafs labeled with decision class. A classification and regression tree (CART) is a type of non-parametric decision tree for producing regression trees or classification and depends on a categorical or numeric dependent variable. These models are attained through recursive data partitioning where a simple prediction model fits in each partition. As a result, the portioning can be seen on the decision tree. The classification trees are designed for dependent variables which have a finite number of unordered values based on prediction errors determined based on misclassification cost. Loh pointed out that regression trees are used for dependent variables that take an ordered discrete or continuous value. In addition, it also takes prediction error and is basically determined through the squared difference between observed and predictive values.

This affinity predictive theory was introduced by Prof. Larbani and Prof. Chen in 2006, for classification and discussion on the set as the distance between the entities. They further supported the theory by stating and calculating arithmetical or abstract measurements. Dissimilarly, some other machine learning methods initially presented the likelihood to propose a time-dependent set theory. It also refers to the relationship between set and elements which it belongs. The affinity approach is used for classification and prediction. Furthermore, the affinity set is also used to investigate the relationship between output and input dataset. Hen et al. (2009) proposed a predictive model to diagnose and associate the accuracy results with SVM, an NN, a rough set (Rosetta), and logistic regression. In addition, the researchers also discussed that the affinity set model is accurate than the ANNs.

van der Ploeg et al. [24] have used a logistic regression predictive model, decision tree predictive model, ensemble predictive model, support vector machine predictive model, and ANN predictive model with 15 datasets. For evaluating the predictive performance, they used AUC (area under the receiver operating characteristic curve). Lu et al. [25] used naive Bayes (NB), artificial neural network (ANN), decision tree, and logistic regression for predicting 6-month (after TBI) functional outcomes. The overall 34.8% functional outcomes of patients are achieved, and 25.2% is the overall mortality; ANN is an effective model with 83.50 sensitivity, 83.50% specificity, and 96.13% AUC. On the other hand, for mortality, the best model is NB with 91.14% AUC, 81.17% sensitivity, and 90.65% is specificity. Chong et al. [26] studied that the predictors are from moderate to severe in TBI, Emergency Department (ED), where the population's age is <16 years from 2006 to 2014. The regression model is used in this study, and its performance is compared with the receiver operating characteristic (ROC) analysis. The researchers used moderate to severe TBI surveillance head injury patient database from 2006 to 2014. Timothy et al. (2015) discussed mild TBI

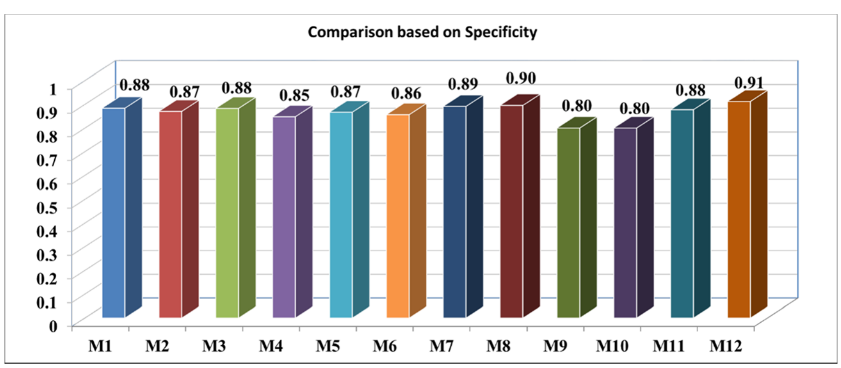

Fig. 7 Average specificity of 10-fold cross-validation based on balance datasets

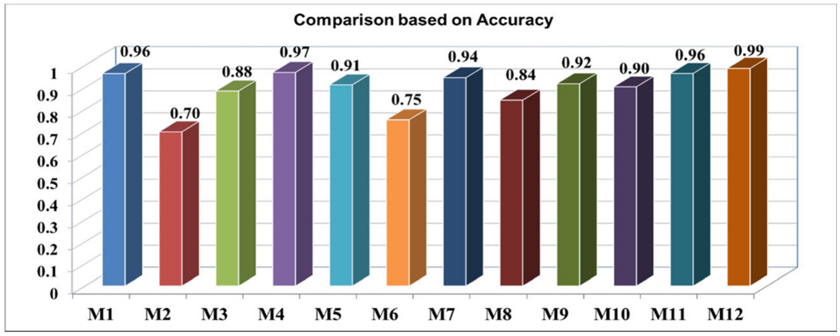

Fig. 8 Average of accuracy of 10-fold cross-validation based on thyroid datasets

patients by GCS, where 50,496 patients with 8.8% rate of neurosurgical intervention are included. In addition, the authors in this study discussed that the mild TBI patients and their injury pattern are related with neurosurgical intervention. The patients suffered from subarachnoid hemorrhage or cerebral contusions much less and need more neurosurgical intervention. Furthermore, it is also observed that the age is not important after taking other patient factors.

Gavin et al. (2015) discussed that gait disorder was related with TBI and categorized into distinct and relevant subgroups. Furthermore, the cross-sectional cohort method is used to compare the TBI patients in order to collect physiotherapy for mobility limitations. A total of 102 TBI patients are involved in this study. The patient pelvis and bilateral lower limb kinematic data are determined by a VICON motion analysis system where every patient walked to select any speed. To carry out this study, a multi-class support vector machine predictive model is designed to automatically and systematically establish the clinical classification. The results of this study indicated that, regardless of the significant variability in gait disorders following TBI, they have the ability to generate a clinical classification by six distinct gait deviation subgroups. Furthermore, these are also able to establish 82% accuracy in TBI patients with related gait disorders by a multi-class support vector machine and with a predictive model.

Hassanzadeh et al. [27] carried out a study to find out the best predictive model to identify clinical disorders resulting in death and trauma in patients. The 1073 trauma patients are hospitalized in the Poursina Hospital in Rasht, where 52 have recorded clinical conditions (features). They used decision tree, K-nearest neighbor, and neural network predictive models. This study also highlighted that there is not any significant relationship between duration of hospitalization and mortality. Among the classification methods, decision tree and K-nearest methods are recognized to have death cases with a higher precision (i.e., 91 and 89%, respectively). In addition, this study recommended that the decision tree model as a predictive model has better predictive performance.

Balvers et al. [28] tried to determine the hemoglobin level (Hb) and transfusion threshold from the neurologic outcome. These outcomes aim to improve the TBI patient neurologic outcomes especially for future transfusion trials. This study defined anemia within 24 h post injury with different *b* values such as ≤9 g/dl level belonging to severe anemia or ≤10 g/dl considered as moderate anemia. The logistic regression predictive model is used for calculating the relationship of neurologic outcome and anemia. The AUC curve and Youden index as receiver operating characteristics are utilized as an optimal transfusion threshold with 261 TBI patients.

Proposed accurate and dynamic predictive model

An accurate and dynamic predictive model (APM) is proposed to improve the predictive performance. In this proposed model, 12 predictive models are combined together to predict the TBI outcomes and the 10-fold cross-validation is used to

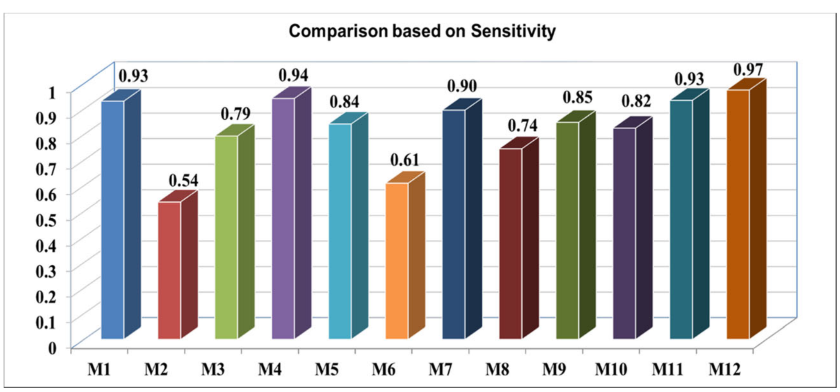

Fig. 9 Average of sensitivity of the10-fold cross-validation based on thyroid datasets

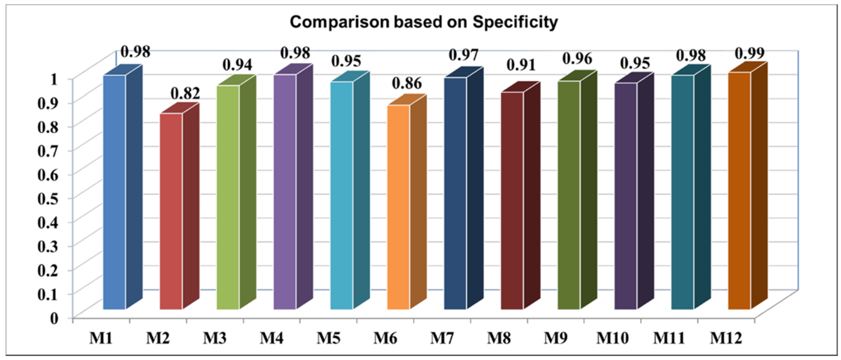

Fig. 10 Average of specificity of 10-fold cross-validation based on thyroid datasets

validate the model. The combined predictive models are artificial neural network (M1), fuzzy model (M2), ensemble model (M3), naive Bayes model (M4), discriminant analysis model (M5), neuro fuzzy model (M6), decision tree model (M7), affinity model (M8), KNN model (M9), multiclass SVM (M10), and logistic regression (M11). These predictive models are used successfully with ten different datasets. These datasets are IRIS, Balance, Thyroid, TEA, CTG-JMI, CTG-CMIM, CTG-DISR, TBI-JMI, TBI-CMIM, and TBI-DISR.

Three featured selection methods are suggested in [29, 30] with these datasets to contain more than six features. These feature selection methods are joint mutual information (JMI), Double Input Symmetrical Relevance (DISR), and Conditional Mutual Info Maximization (CMIM). The predictive performance of these models is evaluated according to accuracy, sensitivity, and specificity. Friedman, "Iman and Davenport," and Holm statistical tests are carried out to verify the predictive performance enhancement and compare existing models.

Abstractly, the APM (M12) model classifies a combination of multiples from the 11 most famous predictive models by a dynamic weighted multi-criteria decision-making method. Mathematically, APM can be formulated as follows:

M_j= is the predictive models (criteria) where $j = \{1, \ldots, m\}$ and m is number of predictive models. Accurate and dynamic predictive framework shows in Fig 1.

$M1$: *Artificial neural network*
$M2$: *Fuzzy model*
$M3$: *Ensemble model*
$M4$: *Naive Bayes model*
$M5$: *Discriminant analysis model*
$M6$: *Neuro fuzzy model*
$M7$: *Decision tree model*
$M8$: *Affinity model*
$M9$: *KNN model*
$M10$: *Multi SVM*
$M11$: Logistic regression

1. *Calculating the accuracy of predictive models:*

Calculating the accuracy Acc_j of predictive models M_j is based on Eq. 1:

$$Acc_j = \left(\sum_{i=1}^{n} \mathrm{TP}\,(i)\right) + \left(\sum_{i=1}^{n} \mathrm{TN}\,(i)\right) \Big/ \left(\sum_{i=1}^{n} (\mathrm{TP}\,(i) + \mathrm{FN}\,(i) + \mathrm{FP}(i) + \mathrm{TN}\,(i)\right) \quad (1)$$

where n is the number of the outcomes and $1 \leq i \leq n$

2. *Calculating the sensitivity of predictive models*

The sensitivity $\mathrm{Sens}_j$of predictive models M_j is calculated based on the following equation:

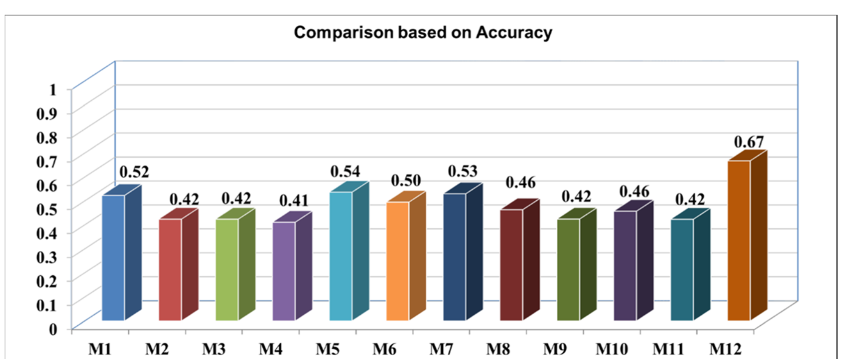

Fig. 11 Average of accuracy of 10-fold cross-validation based on TEA datasets

$$Sens_j = {\left(\sum_{i=1}^{n} \text{TP }(i)\right)}\Big/_{\left(\sum_{i=1}^{n}(\text{TP }(i)+\text{FN}(i))\right)} \quad (2)$$

3. *Calculating the specificity of predictive models:*

Specificity Spec_j of predictive models M_j is calculated based on the following equation:

$$Spec_j = {\left(\sum_{i=1}^{n} \text{TN }(i)\right)}\Big/_{\left(\sum_{i=1}^{n}(\text{FP }(i)+\text{TN}(i))\right)} \quad (3)$$

4. *Calculating the weights of predictive models*

The weight W_j of predictive models M_j is calculated based on Eq. 4:

$$W_j = \frac{\text{Acc}_j + Sens_j + Spec_j}{3} \quad (4)$$

where W_j= is the weight of predictive models

5. *Calculating the adjusted weights of predictive models*

The adjusted weight of predictive models $\text{WWW}_{j\text{vp}}$ is the weight of predictive models where the maximum weight of W_j has the decision power dp and $dp = 1, 2, \ldots, m$.

6. *Transformation and normalization*

Linear scale transformation is used for normalization and is considered a straightforward process to divide the product of a definite criterion by its maximum value, on the condition that the criterion is defined as the benefit criterion (the larger x_j , the greater preference); then, the transformed result of x_{ij} is as follows:

$$r_{ij} = \frac{x_{i,j}}{x^*_j} \; where, x^*_j = \max_i \; x_{i,j} \quad (5)$$

$0 < r_{ij} < 1$, the value of r_{ij} will be between 0 and 1.

7. *Calculating the most preferred outcome*

The most preferred outcome $O*_{vp}$, will be selected such as

$$O*_{vp} = \left\{ O_{idp} \middle| \max_i \sum_1^m \text{WWW}_{j\,dp}{}^* \, r_{i,j\,(t)} \right\} \quad (6)$$

where M_j is the predictive model and $r^*_{i,j(t)}$ is the outcome of the i th and j th predictive model (criteria) at time (t) while O_i is the score outcome for the decision power dp and $1 \le dp \le m$. The final value of the decision vote depends on the best predictive performance.

$r^*_{ij\ (t)}$ Can be changed based on the decision-maker

$$\begin{aligned} r^*ij(t) &= \min r^*ij(t) \\ r^*ij(t) &= \max r^*ij(t) \\ r^*ij(t) &= mean\, r^*ij(t) \\ r^*ij(t) &= median\, r^*ij(t) \end{aligned}$$

Experiments and results

In the first experiment, 12 predictive models are used with the IRIS dataset to predict the outcomes from iris plant, and a 10-fold cross-validation was used to validate the model. A comparison between the proposed predictive model (M12) with artificial neural network (M1), fuzzy model (M2), ensemble model (M3), naive Bayes model (M4), discriminant analysis model (M5), neuro fuzzy model (M6), decision tree model (M7), affinity model (M8), KNN model (M9), multiclass SVM (M10), and logistic regression (M11) in terms of average of accuracy of the 10-fold cross-validation based on the TBI-CMIM datasets shows in Fig. 2. In addition, a comparison between M12 and other predictive models in terms of average sensitivity of the 10-fold cross-validation based on TBI-CMIM datasets is shown in Fig. 3. Finally, a comparison of the proposed model M12 with a benchmark model in terms of average of specificity of the 10-fold cross-validation based on TBI-CMIM datasets is illustrated in Fig. 4.

In a nutshell, these comparisons indicated that the proposed predictive models outperform the existing predictive models in terms of sensitivity, specificity, and accuracy of evaluation metrics. In addition, the proposed affinity predictive model is able to resolve the TBI multi-class prediction.

In the second experiment, 12 predictive models are used together with the balance dataset to predict the psychological experimental outcomes and the 10-fold cross-validation to validate the model. In this experiment, a comparison between the proposed predictive model (M12) in terms of average of accuracy of the 10-fold cross-validation based on the balance datasets is shown in Fig. 5. In addition, a comparison between the proposed predictive models and other predictive models in terms of average of sensitivity of the 10-fold cross-validation based on the balance datasets is shown in Fig. 6. Finally, a comparison between M12 and benchmarks in terms of average of specificity of the 10-fold cross-validation based on the balance datasets is illustrated in Fig. 7.

In a nutshell, these comparisons show that the proposed predictive model outperforms the existing predictive models in terms of sensitivity, specificity, and accuracy of evaluation metrics. In addition, the proposed affinity predictive model is able to resolve the TBI multi-class prediction.

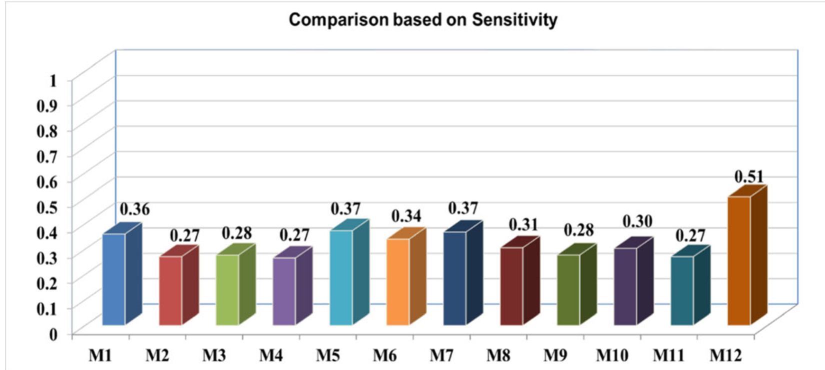

Fig. 12 Average of sensitivity of 10-fold cross-validation based on TEA datasets

In the third experiment, 12 predictive models are used with the thyroid dataset to predict a given patient with three outcomes (1) normal, (2) suffering from hyperthyroidism, (3) or suffering from hypothyroidism and the 10-fold cross-validation to validate the model. The comparison between the proposed predictive models (M12) and existing models in terms of average of accuracy of the 10-fold cross-validation based on the thyroid datasets is shown in Fig. 8. In addition, a comparison between M12 and other predictive models in terms of average of sensitivity of the 10-fold cross-validation based on thyroid datasets is shown in Fig. 9. Finally, a comparison between the M12 models and the benchmarks in terms of average of specificity of the 10-fold cross-validation based on thyroid datasets is illustrated in Fig. 10.

In a nutshell, these comparisons indicate that the proposed predictive model outperforms the existing predictive models in terms of sensitivity, specificity, and accuracy of evaluation metrics. In addition, the proposed affinity predictive model is able to resolve the TBI multi-class prediction.

In the fourth experiment, 12 predictive models are used with the TEA dataset to predict a psychological experimental outcomes and a 10-fold cross-validation was used to validate the model. A comparison between the proposed predictive models (M12) and existing models in terms of average of accuracy of the 10-fold cross-validation based on TEA datasets is shown in Fig. 11. In addition, a comparison between the proposed M12 and other predictive models in terms of average sensitivity of the 10-fold cross-validation based on TEA datasets is shown in Fig. 12. Finally, a comparison between the proposed predictive models and benchmarks in terms of average of specificity of 10-fold cross-validation based on TEA datasets is illustrated in Fig. 13.

In a nutshell, these comparisons show that the proposed predictive models outperform the existing predictive models in terms of sensitivity, specificity, and accuracy of evaluation metrics. In addition, the proposed affinity predictive model is able to resolve the TBI multi-class prediction.

In the fifth experiment, 12 predictive models are used with the CTG dataset after using a featured selection method which is joint mutual information (JMI) and a 10-fold cross-validation was used for validation. A comparison between the proposed model (M12) and existing models in terms of average of accuracy of the 10-fold cross-validation based on TEA datasets is shown in Fig. 14. In addition, a comparison between M12 and other predictive models in terms of average sensitivity of the 10-fold cross-validation based on TEA datasets is shown in Fig. 15. Finally, a comparison between the proposed predictive models and the benchmarks in terms of average of specificity of the 10-fold cross-validation based on TEA datasets is illustrated in Fig. 16.

In a nutshell, these comparisons show that the proposed predictive model outperforms the existing predictive models

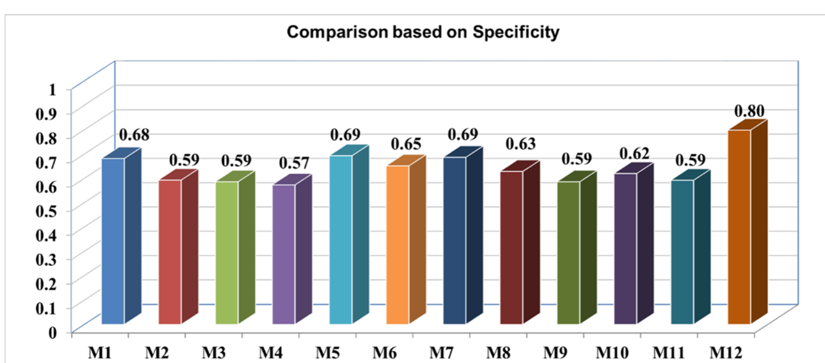

Fig. 13 Average of specificity of 10-fold cross-validation based on TEA datasets

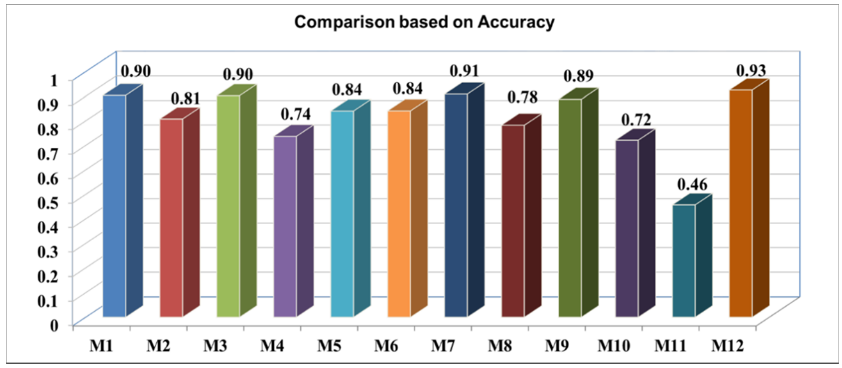

Fig. 14 Average of accuracy of 10-fold cross-validation based on CTG-JMI datasets

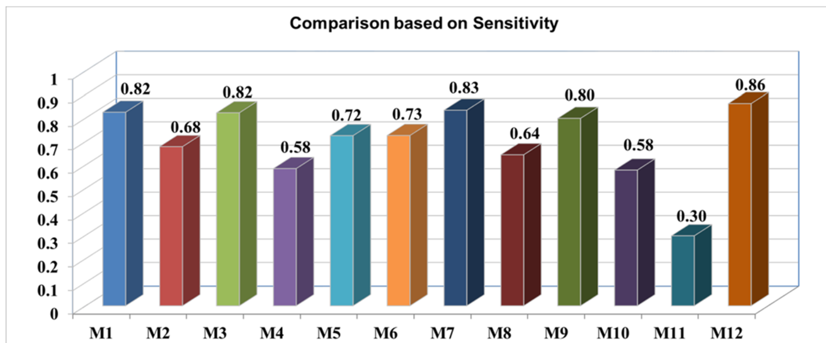

Fig. 15 Average of sensitivity of 10-fold cross-validation based on CTG-JMI datasets

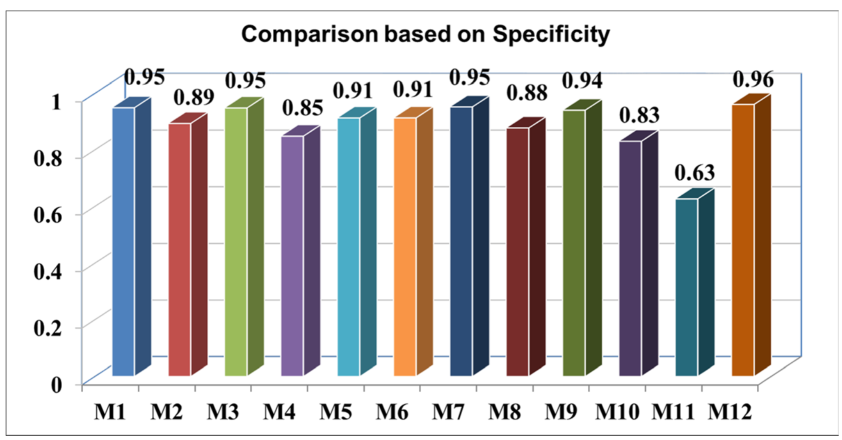

Fig. 16 Average of specificity of the10-fold cross-validation based on CTG-JMI datasets

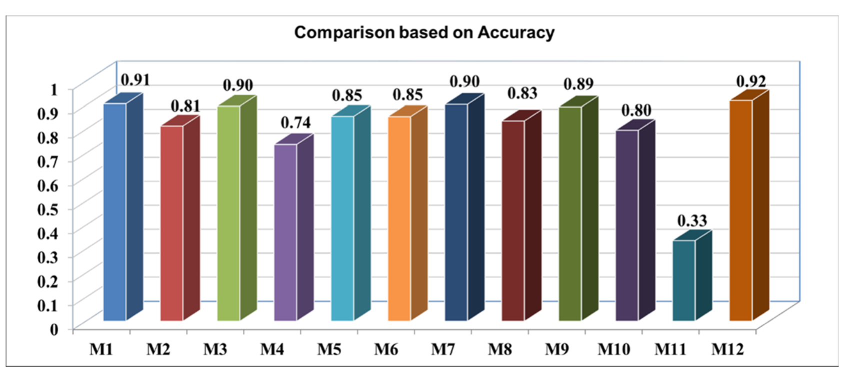

Fig. 17 Average of accuracy of the10-fold cross-validation based on CTG-CMIM datasets

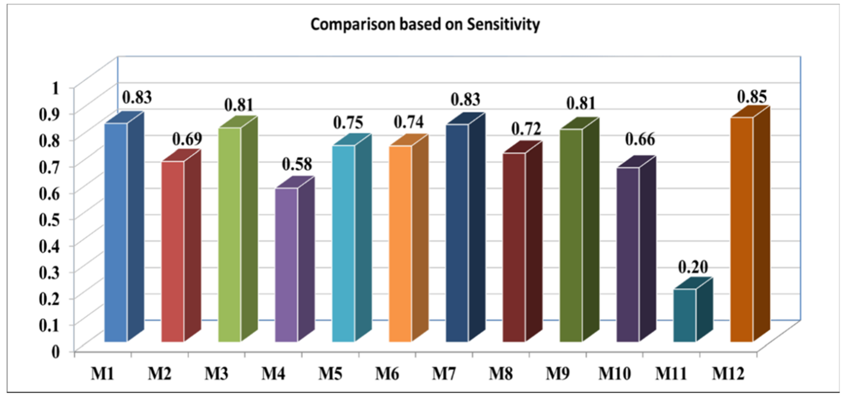

Fig. 18 Average of sensitivity of the 10-fold cross-validation based on CTG-CMIM datasets

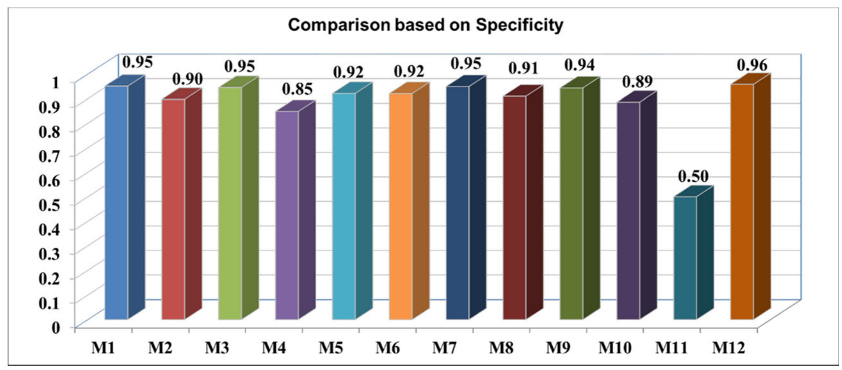

Fig. 19 Average of specificity of the 10-fold cross-validation based on CTG-CMIM datasets

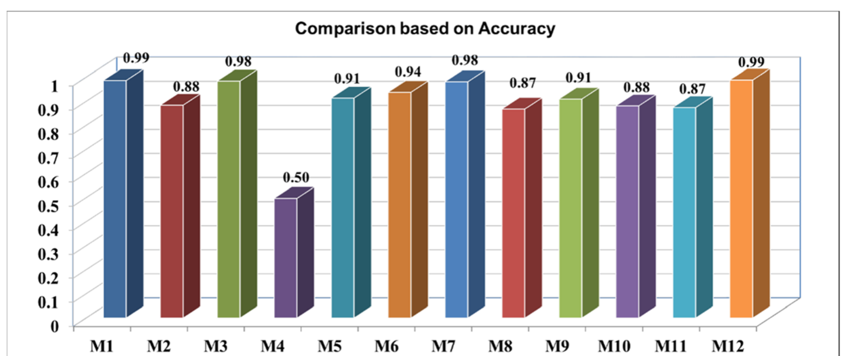

Fig. 20 Average of accuracy of the 10-fold cross-validation based on CTG-DISR datasets

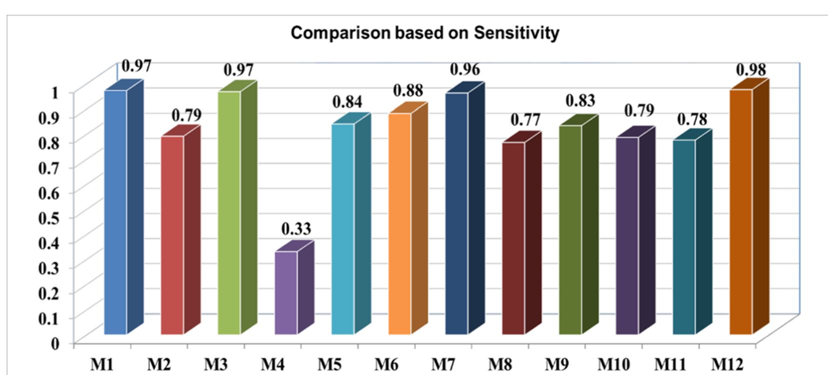

Fig. 21 Average of sensitivity of the10-fold cross-validation based on CTG-DISR datasets

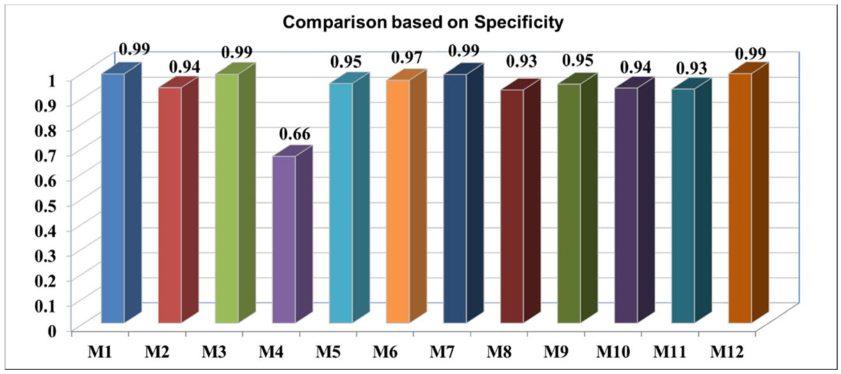

Fig. 22 Average of specificity of the 10-fold cross-validation based on CTG-DISR datasets

in terms of sensitivity, specificity, and accuracy of evaluation metrics. In addition, the proposed affinity predictive model is able to resolve the TBI multi-class prediction.

In the sixth experiment, 12 predictive models are used with the CTG dataset after using the feature selection method which is Conditional Mutual Info Maximization (CMIM) and a 10-fold cross-validation was used for validation. A comparison between the proposed (M12) and existing models in terms of average of accuracy of the 10-fold cross-validation based on CTG-CMIM datasets is shown in Fig. 17. In addition, a comparison between M12 and other predictive models in terms of average sensitivity of the 10-fold cross-validation based on CTG-CMIM datasets is shown in Fig. 18. Finally, a comparison between M12 and the benchmarks in terms of average of specificity of the 10-fold cross-validation based on CTG-CMIM datasets is illustrated in Fig. 19.

In a nutshell, these comparisons show that the proposed predictive model outperforms the existing predictive models in terms of sensitivity, specificity, and accuracy of evaluation metrics. In addition, the proposed affinity predictive model is able to resolve the TBI multi-class prediction.

In the seventh experiment, 12 predictive models are used with the CTG dataset after the feature selection method including Double Input Symmetrical Relevance (DISR) and the 10-fold cross-validation was used for validation. A comparison between the proposed predictive models (M12) and existing models in terms of average of accuracy of the 10-fold cross-validation based on CTG-DISR datasets is shown in Fig. 20. In addition, a comparison between the proposed predictive models and other predictive models in terms of average sensitivity of the 10-fold cross-validation based on CTG-DISR datasets is presented in Fig. 21. Finally, a comparison between the proposed predictive models and the benchmarks in terms of average of specificity of the 10-fold cross-validation based on CTG-DISR datasets is illustrated in Fig. 22.

In a nutshell, these comparisons show that the proposed predictive models outperform the existing predictive models in terms of sensitivity, specificity, and accuracy of evaluation metrics. In addition, the proposed affinity predictive model is able to resolve the TBI multi-class prediction.

In the eighth experiment, 12 predictive models are used with the TBI dataset for predicting the outcomes of traumatic brain injury with the degree of residual disability and a 10-fold cross-validation for validation. Three featured selection methods are used with the TBI dataset including joint mutual information (JMI), Double Input Symmetrical Relevance (DISR), and Conditional Mutual Info Maximization (CMIM).

Conclusion

In this paper, a comprehensive framework of an accurate and dynamic predictive model (APM) is presented and portrayed. A dynamic weighted sum multi-criteria decision-making method is used with multiple predictive models to obtain a better predictive performance for prediction and classification compared to existing models. Then, a mathematical formulation of APM is presented. Different experiments are conducted to test the APM performance based on IRIS, Balance Scale Dataset, Thyroid, teaching evaluation assessment, CTG-JMI, CTG-CMIM, and CTG-DISR datasets. The 10-fold cross validation is used to validate the proposed model. The predictive model performance is evaluated in terms of accuracy, sensitivity, and specificity of evaluation metrics using the confusion matrix. The proposed predictive models achieved the best average ranking which is considered significantly as the best predictive model among the whole multiple models in terms of accuracy, sensitivity, and specificity. The proposed model will be helpful in the medical field to predict the TBI outcomes. In the future, we will develop a more accurate model for other serious diseases in medical science. In addition, we will develop more models for other diseases as well.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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