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Severity Classification of Myocardial Infraction Using ML Technique: A Comparative Analysis

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Abstract*— MI is a critical cardiovascular condition that leads to millions of deaths worldwide. Early and accurate diagnosis of MI is crucial to prevent adverse outcomes such as heart failure and fatality. Traditional diagnostic methods, such as angiography, are invasive, costly, and may have associated risks. Therefore, researchers have turned to MLand data mining techniques to develop alternative diagnostic approaches. This paper proposes ELM for the classification of MI severity. To find the most informative subsets of features, the feature ranking algorithms namely MRMR, Relief-F, and Fisher are used on the publicly available MI dataset from the UCI ML Repository. The proposed model is evaluated using a 10-fold cross-validation technique. Comparative analysis is conducted to assess the performance of the ELM classifier with SVM, Random Forest, and XG Boost robust classifiers. The results show the highest accuracy achieved by the ELM model is 99.74% with 40 features selected using the MRMR feature ranking algorithm. However, the highest accuracy achieved by SVM, RF, and XG Boost is 95.09%, 94.1%, and 94.7% respectively. Overall, the proposed ELM model with feature ranking algorithms offers an effective and efficient solution for the severity classification of MI.

***Index Terms*— Myocardial Infraction, Machine Learning, Extreme Learning Machine, Support Vector Machine, Maximum Relevance Minimum Redundancy**

I. INTRODUCTION AND RELATED WORK

A Myocardial infarction (MI), commonly known as a heart attack, is a serious condition in which blood flow to the heart muscle is blocked and heart tissue is damaged. MI is one of the leading causes of death worldwide, causing approximately 15.2 million deaths annually (World Health Organization, 2021). The high mortality rate from MI is primarily due to disease-related complications such as cardiac arrhythmia, heart failure, and cardiac arrest. Management of MI is challenging due to its unpredictability and the multitude of factors that contribute to disease onset and progression. Clinicians rely on a variety of diagnostic tools to assess disease severity and predict likely adverse outcomes.

Machine learning (ML) algorithms offer a promising approach to improving the accuracy of MI diagnosis. A ML algorithm is a subset of the artificial intelligence domain that can learn from data and use that to make predictions. ML algorithms can analyze large amounts of data and severity classification of MI. However, most of the studies on MI severity classification have used other datasets that focus on using ML algorithms to predict outcomes based on a limited set of characteristics. To improve the accuracy of MI classification, it is important to consider a broader set of features related to disease complexity.

The paper [1] proposes a deep CNN model for classifying MI using multi-lead ECG signals. The model achieves over 99% accuracy on training and test data, showing robust performance. Lead V4 and V5 exhibit the highest classification performance. The proposed model is deemed valuable for aiding the classification of MI, however, research on larger datasets is recommended for improved performance and clinical integration.

The paper [2] proposes a new technique for early and accurate detection of inferior MI (IMI) using ECG signals. The method employs stationary wavelet transform and ML with SVM and KNN classifiers. Evaluation of the PTB-DB dataset shows high performance with an area under the ROC curve of 0.9945 (KNN) and 0.9994 (SVM) in the class-oriented approach. The subject-oriented approach achieves an average accuracy of 81.71%.

The paper [3] presents a novel approach using CNN to develop an automatic diagnostic approach for classifying MI (MI) and cardiomyopathy based on ECG data obtained at different time intervals. The researchers utilized the ECG-VIEW II database and trained the CNN model on a division of the data into training, validation, and test sets. CNN achieved high accuracy in differentiating between MI and cardiomyopathy, with an average accuracy of 91.1% using 10-fold cross-validation. The performance with large datasets and additional features could improve the CNN performance.

This paper proposes an Extreme Learning Machine (ELM) to classify the severity of MI using the MI complications dataset from the UCI ML repository. To find the most discriminative features in the datasets, three feature ranking algorithms namely MRMR, Relief-F, and Fisher are employed. Thirty different datasets are prepared by selecting the top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55, and top-60 features from each of the MRMR, Relief-f and fisher feature ranking algorithms. The proposed model performance is compared with the other three models

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namely SVM, RF, and XG Boost with all the thirty datasets. A 10-fold cross-validation technique is used to evaluate the performance. The result shows the superior performance of the proposed ELM model compared to the other three models.

II. METHODOLOGY

2.1 Data Description

This paper uses the MI complications dataset from the UCI ML repository that contains the record of 1700 patients. There are a total of 111 features in this dataset. The dataset has eight severity classes namely (i) unknown (alive) (1429), (ii) cardiogenic shock (110), (iii) pulmonary edema (18), (iv) myocardial rupture (54), (v) progress of congestive heart failure (23), (vi) thromboembolism (12), (vii) asystole (27) and (viii) ventricular fibrillation (27)..

2.2 Data Preprocessing

Data preprocessing is crucial to ensure the quality and reliability of the dataset. In this paper, missing values are handled by using the mean imputing technique. First, any missing values in the dataset are handled by imputing them with suitable values. Outliers, which are extreme values that can adversely affect performance, are handled by replacing them with mean values. To facilitate performance, numerical features in the dataset are normalized to ensure they are on a similar scale. This prevents certain features from dominating the model training process due to their larger magnitude. Features having categorical variables are converted into numerical ones.

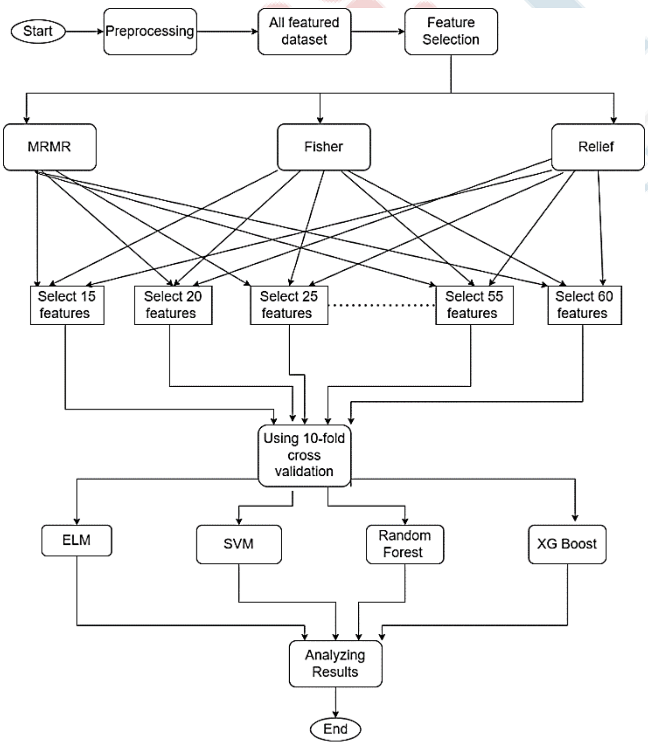

Fig. 1 Workflow (name of algorithm)

2.3 Feature selection

As Feature selection is performed to identify the most relevant and informative subsets of features for MI severity classification. The selection of informative features may improve the performance of the ML models[10]. In this paper feature ranking algorithm MRMR, Relief-F, and Fisher. To analyze the best set of features, several feature subsets are fed to the proposed ELM model, SVM, RF, and XG Boost.

The MRMR feature ranking algorithm plays a vital role in classification tasks. It tackles the challenges of overfitting and diminished model performance by selecting relevant features while minimizing redundancy.

MRMR feature ranking algorithm, is a supervised filter-based method. MRMR identifies features based on their relevance and redundancy values and aims to maximize their relevance to the target variable while minimizing redundancy. For a dataset containing 'd' features, the goal is to select a subset of 'm' features that yield the highest score, taking into account relevance and redundancy. Finding the optimal subset requires a large amount of computation, it uses a heuristic approach to estimate each feature score. The MRMR algorithm tries to minimize the within-class variance and maximize the between-class variance. The score for the feature 'i' is calculated using Equation 1.

$$S(i) = R(i) - \frac{1}{k}\sum_{j=1}^{k} M(i,j) \qquad \text{----(1)}$$

Where:

- S(i) is the mRMR score of features "i".
- R(i) is the relevance score of features "i" concerning the target variable.
- k is the number of selected features in the current subset.
- M(i,j) represents the redundancy score between feature "i" and the previously selected feature "j".

Fisher feature selection technique focuses on maximizing the ratio of between-class variance and within-class variance. The fisher score is calculated by the Equation 2

$$\text{Si}= \frac{\sum \text{nj}(\mu\text{ij}-\mu\text{i})^2}{\sum \text{nj}*\rho 2\text{ij}} \qquad \text{-------(2)}$$

Where:

- µij is the mean of the i-th feature in the j-th class
- ρij is the variance of the i-th feature in the j-th class
- nj is the number of instances in the j-th class
- µi is the mean of the i-th feature.

The relief-F feature selection technique assigns weights to features based on their ability to distinguish between instances of the same and different classes.

The ranking of top-60 features that are considered for the evaluation of the performance of the proposed model is given in Table 1.

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Table 1: The top-60 features selected by the MRMR feature ranking technique

Feature Name	Feature Ranking by MRMR
np05	1
S_AD_ORIT	2
S_AD_KBRIG	3
AGE	4
ROE	5
D_AD_ORIT	6
D_AD_KBRIG	7
NA_BLOOD	8
L_BLOOD	9
TIME_B_S	10
DLIT_AG	11
STENOK_AN	12
ant_im	13
inf_im	14
GB	15
FK_STENOK	16
lat_im	17
INF_ANAM	18
IBS_POST	19
NA_R_1_n	20
K_BLOOD	21
post_im	22
NOT_NA_1_n	23
R_AB_1_n	24
ZSN_A	25
ritm_ecg_p_01	26
NOT_NA_KB	27
NA_KB	28
ANT_CA_S_n	29
GIPO_K	30
SEX	31
GEPAR_S_n	32
LID_S_n	33
LID_KB	34
ASP_S_n	35
ZSN	36
R_AB_2_n	37
ritm_ecg_p_07	38
TRENT_S_n	39
NOT_NA_2_n	40
endocr_01	41
B_BLOK_S_n	42
NA_R_2_n	43
n_r_ecg_p_03	44
NOT_NA_3_n	45
ALT_BLOOD	46
NITR_S	47
R_AB_3_n	48
zab_leg_01	49
OTEK_LANC	50
REC_IM	51
FIBR_PREDS	52
NA_R_3_n	53
P_IM_STEN	54
n_p_ecg_p_07	55
zab_leg_02	56
MP_TP_POST	57
O_L_POST	58
ritm_ecg_p_02	59
n_p_ecg_p_12	60

2.4 Proposed Model

This paper proposes the ELM model for the severity classification of MI and compares it with the robust classifiers namely SVM, RF, and XGBoost. These algorithms are known for their ability to handle complex relationships between features and target variables. The choice of the most appropriate algorithm depends on factors such as the dataset characteristics, computational efficiency, interpretability, and prior knowledge about the problem domain.

2.4.1 Extreme learning machine

The architecture of the ELM [4] is based on the single-layer feed-forward neural network (SLFN) as shown below in Figure 2.

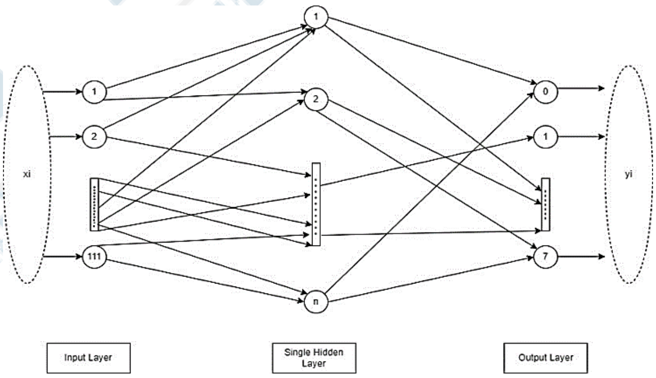

Figure 2: Architecture of Single Layer Feed Forward Neural Network

ELM demonstrates a swifter learning pace compared to the conventional SLFN learning method, like the back-propagation algorithm. It is recognized for its simplicity, better performance, and strong generalization ability. ELM is applied in many domains including bioinformatics, the prediction of hydrological phenomena, as well as robotics and control systems[5].

2.4.2 SVM

SVM [6] is a powerful tool for classifying data points. It finds a hyperplane that best separate different classes while maximizing the margin between them. SVM is especially useful in complex datasets like cancer genomics, where it excels at recognizing subtle patterns. It can also handle nonlinear relationships using kernel functions, which map data into higher-dimensional spaces.

2.4.3 Random Forest

Random Forest [7] is an ensemble learning method in ML. It creates multiple decision trees using subsets of the training data. Each tree is constructed by considering random subsets of features at each split. During prediction, RF uses a voting mechanism for classification or averaging for regression. This approach is robust to noisy data. RF is known for its accuracy, ability to handle large datasets, and resistance to overfitting.

2.4.4 XGBoost

XGBoost [8] is a powerful tree boosting system used in ML for tasks like classification, regression, and ranking. It builds a series of decision trees on different data subsets, combining their predictions for results. XGBoost achieves high accuracy through techniques like regularization and gradient boosting. It's highly scalable and capable of handling large datasets with billions of examples and numerous features. This makes it popular for tasks like classification, image recognition, and natural language processing. XGBoost is flexible, interpretable, and excels in achieving state-of-the-art results in various ML tasks.

2.5 Model Training and Evaluation

To classify the severity of MI, this paper proposes an ELM model with feature ranking algorithms for MI severity classification. The model is trained on the MI dataset from the UCI ML Repository. To find the most informative subsets of features, three feature ranking algorithms namely MRMR, Relief-F, and Fisher are applied. The model is trained with various feature subsets. These feature subsets contain top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55, and top-60 features ranked by MRMR, relief-F and fisher feature ranking algorithms. All the models are trained with the above-mentioned feature subsets and evaluated with a 10-fold cross-validation technique[9].

III. RESULTS AND DISCUSSIONS

Table 2 shows the accuracy achieved by different ML classifiers (SVM, Random Forest, XGBoost, and ELM) on the different feature subsets obtained by the MRMR feature ranking algorithm. The feature subsets have top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55 and top-60 features. The highest accuracy achieved by ELM is 99.78% with top-40 features. The highest accuracy achieved by SVM is 95.09% with top-40 features. The highest accuracy achieved by RF is 94.11% with top-25 features. The highest accuracy achieved by XGBoost is 94.70% with top-60 features. The highest accuracy achieved by the ELM classifier is better than the other classifiers. It is observed that the accuracy achieved by ELM is better with all feature subsets except with the top-20 feature subset.

Table 2: Accuracy comparison of the classifiers on different feature subsets obtained by the mRMR feature ranking algorithm (Using 10-CV)

S. NO.	No of Features	SVM	Random Forest	XG Boost	ELM
1	15	93.5	92.94	93.72	99.11
2	20	93.13	92.54	93.13	92.64
3	25	94.50	94.11	93.72	98.82
4	30	94.70	93.92	93.72	96.17
5	35	94.90	93.13	94.31	97.64
6	40	95.09	93.33	94.11	99.78
7	45	93.52	93.72	93.92	97.94
8	50	92.54	92.94	93.72	99.41
9	55	93.52	93.13	94.11	97.35
10	60	92.94	93.13	94.70	96.17

Table 3 shows the accuracy achieved by different ML classifiers (SVM, Random Forest, XGBoost, and ELM) on the different feature subsets obtained by the Relief-F feature ranking algorithm. The feature subsets have top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55 and top-60 features. The highest accuracy achieved by ELM is 97.64% with top-60 features. The highest accuracy achieved by SVM is 90.78% with top-55 features. The highest accuracy achieved by RF is 90.98% with top-30 features. The highest accuracy achieved by XGBoost is 91.96% with top-40 features. The highest accuracy achieved by the ELM classifier is better than the other classifiers.

Table 3: Accuracy comparison of the classifiers on different feature subsets obtained by the Relief-F feature ranking algorithm (Using 10-CV)

S. NO.	No of Features	SVM	Random Forest	XG Boost	ELM
1	15	89.60	90.19	90	77.05
2	20	90	90.39	90	62.05
3	25	90	90.78	90.78	87.94
4	30	90.19	90.98	90.78	75.88
5	35	89.8	90	90.98	78.82
6	40	90.58	90.78	91.96	90.58
7	45	90.39	90.19	91.56	93.82
8	50	90.19	90	91.76	90.88
9	55	90.78	89.8	90.78	95.88
10	60	90	89.01	91.37	97.64

Table 4 shows the accuracy achieved by different ML classifiers (SVM, Random Forest, XGBoost, and ELM) on the different feature subsets obtained by the Relief-F feature ranking algorithm. The feature subsets have top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55 and top-60 features. The highest accuracy achieved by the ELM classifier is 99.11% with the top-55 features. The highest accuracy achieved by the SVM classifier is 91.37% with top-20, top-35, and top-40 features. The highest accuracy achieved by RF is 92.76% with top-30 features. The highest accuracy achieved by XGBoost is 92.94% with top-30 features. The highest accuracy achieved by the ELM classifier is better than the other classifiers. It is observed that the ELM classifier is performing consistently better than other classifiers with top-40, top-45, top-50, and top-60 feature subsets.

Table 4: Accuracy comparison of the classifiers on different feature subsets obtained by the Fisher feature ranking algorithm (Using 10-CV)

S.NO.	No of features	SVM	Random Forest	XG Boost	ELM
1	15	89.80	90.39	90.19	84.11
2	20	91.37	92.15	91.37	42.64
3	25	90.58	91.96	93.13	69.70
4	30	90.39	91.76	92.94	88.52
5	35	91.37	92.15	92.54	53.82
6	40	91.37	90.58	92.54	97.64
7	45	90.78	91.17	92.74	98.82
8	50	90.78	91.96	92.54	96.76
9	55	90.98	91.37	92.35	99.11
10	60	90.39	90.39	92.35	71.47

Overall, the highest accuracy achieved by the ELM classifier is better than the other classifiers. The highest accuracy achieved by the ELM classifier with top-60 features ranked by Relief-F is 97.64% and with top-55 features ranked by Fisher is 99.11%. However, with the top-40 features ranked by mRMR, the highest accuracy achieved by the ELM classifier is 99.78%. With mRMR, the ELM classifier achieved better accuracy with only a top-40 feature subset. It is also observed that mRMR is better able to rank the relevant features compared to Relief-F and Fisher feature ranking algorithms as all other classifiers (SVM, RF, and XGBoost) achieved the highest accuracy with feature subsets ranked by mRMR. Therefore, it can be concluded that mRMR is better able to rank the relevant features compared to Relief-F and Fisher feature ranking algorithms.

Figure 3 shows the average accuracy in 10-CV by ELM, SVM, RF, and XGBoost classifiers and accuracies obtained by ELM, SVM, RF, and XGBoost classifiers in each fold of 10-CV. Figure 3 (a) shows each fold accuracies and the mean accuracy of the ELM classifier with the top-40 features subset ranked by the mRMR feature ranking algorithm. It is observed that the ELM classifier achieved the highest accuracy of 100% in 7-folds out of the 10-folds and the mean accuracy is 0.9978. Figure 3(b) shows each fold accuracies and the mean accuracy of the SVM classifier with the top-40 features subset ranked by the mRMR feature ranking algorithm. It is observed that the SVM classifier achieved the highest accuracy of 99% in 1-fold out of the 10-folds and the mean accuracy is 0.9509. Figure 3(c) shows each fold accuracies and the mean accuracy of the RF classifier with the top-25 features subset ranked by the mRMR feature ranking algorithm. It is observed that the RF classifier achieved the highest accuracy of 98.09% in 1-fold out of the 10-folds and the mean accuracy is 0. 9411. Figure 3(d) shows each fold accuracies and the mean accuracy of the XGBoost classifier with the top-60 features subset ranked by the mRMR feature ranking algorithm. It is observed that the XGBoost classifier achieved the highest accuracy of 95.9% in 3-folds out of the 10-folds and the mean accuracy is 0. 9470. It can be observed clearly that the ELM classifier is performing much better than the other classifiers as 100% accuracy is achieved in the highest number of folds (7-folds). This shows that the ELM classifier performance is most consistent compared to other classifiers.

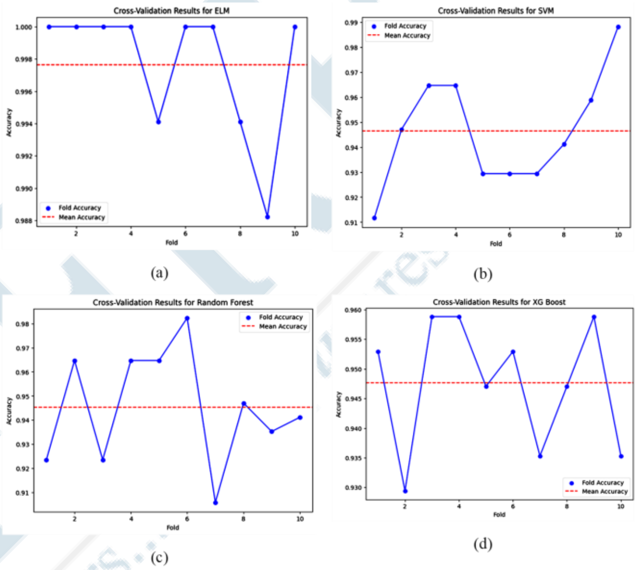

Fig. 3: 10-fold cross-validation for (a) ELM classifier with mRMR (40-features) (b) SVM classifier with mRMR (40-features) (c) RF classifier with mRMR(25-features) (d) XGBoost classifier with mRMR(60-features)

Figure 4, shows the accuracy comparison of classifiers with different feature subsets obtained by feature ranking algorithms mRMR, Relief-F, and Fisher. Figure 4(a) shows the accuracy obtained by ELM, SVM, XGBoost, and RF using top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55, and top-60 feature subsets selected by mRMR feature ranking algorithm. It is observed that ELM outperforms the other classifiers with all feature subsets except the top-20 feature subset. Figure 4(b) shows the accuracy obtained by ELM, SVM, XGBoost, and RF using top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55 and top-60 feature subsets selected by Relief-F feature ranking algorithm. It is observed that SVM, XGBoost, and RF have consistency in accuracy but ELM outperforms them in obtaining the highest percentage with top-45, top-50, and top-60 feature subsets. Figure 4(c) shows the accuracy obtained by ELM, SVM, XGBoost, and RF using top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55, and top-60 feature subsets selected by Fisher feature ranking algorithm. It is observed that ELM outperforms the other

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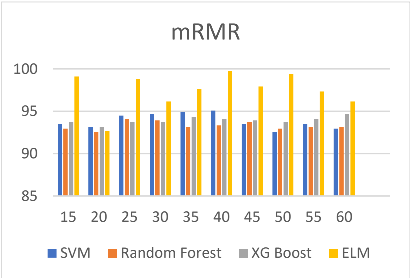
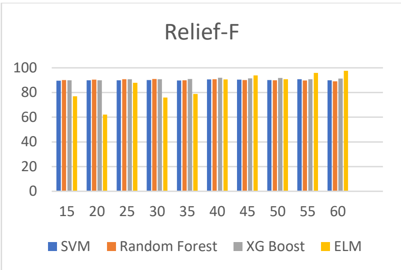
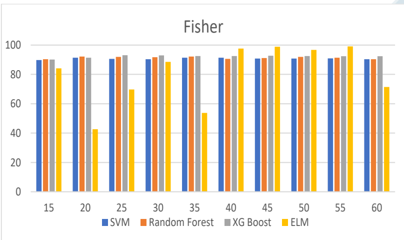
classifiers with top-40, top-45, top-50, and top-55 feature subsets.



(a)



(b)



(c)

Fig. 4: Accuracy comparison of classifiers with different feature subsets (a) mRMR, (b) Relief-F, (c) Fisher

IV. CONCLUSION

This paper proposed ELM for the MI severity classification and compared the performance of other classifiers namely SVM, RF, and XGBoost to evaluate its robustness. To optimize the performance of the classifiers by selecting the relevant features, the paper employs three feature ranking algorithms namely mRMR, Relief-F, and Fisher on MI complications dataset from the UCI ML repository. The paper selected top-15, top-20, top-25, top-30, top-35, top-40, top-45, top-50, top-55, and top-60 feature subsets from each of the feature ranking algorithms. The proposed model achieves the highest classification accuracy of 99.76% with a top-40 feature subset selected by the mRMR feature ranking algorithm. To check any performance enhancement the proposed model was tested on 30-feature subsets. It was found that the proposed model outperformed the other models. The important benefit of the proposed model is that it learns very fast and gives a quick response. In the future, the proposed model may be hybridized with other evolutionary algorithms such as the particle swarm optimization algorithm, Firefly algorithm, genetic algorithm, etc. Also, some other ranking algorithms may be used to determine the important discriminative features in the MI severity classification.

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