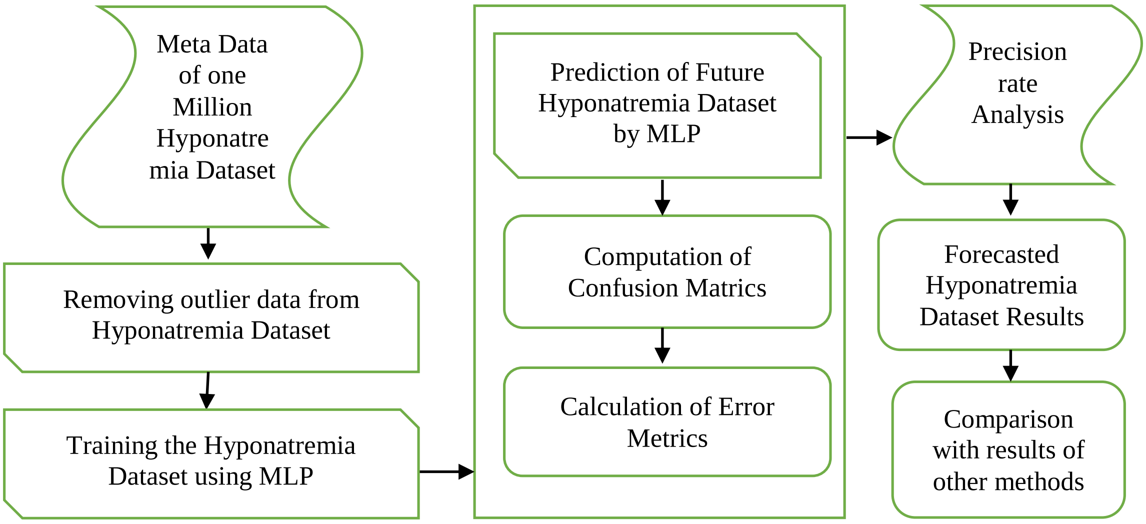

Fig. 1. Block diagram of the proposed model

given to the input layer and computations from the hidden layer. The hidden layer number can be varied (increased/decreased) based on the complexity of the given problem [37]. In general, any neural network model's main objective is to optimize or approximate the given function f(x). Similarly, the multilayer perceptron neural network model will find the best optimized or approximate solution to the given complex problem by using techniques such as classification, regression, or mapping functions [31].

In the proposed MLP based supervised learning technique, each neuron uses a nonlinear activation function and back-propagation for training. The proposed MLP network consists of several chained functions. Let consider a classifier problem y= f(x); here, the output y is driven by the input x and its corresponding mapping solution given by MLP based on the best approximation of the given classifier function. The MLP computes the best-optimized solution as y = f(x; θ), where θ is the learning parameter of the given problem. For example, the three-layer MLP network can be formulated as f(x) = f (x3) (f (x2) (f (x1) (x))). The MLP performs several defined transformation and/or linear summation functions with the inputs in each layer. In MLP, each of these layers is symbolized as y = f(W.x.T + b); where the activation functions are denoted as f, the weights or set of the parameter of the problem are indicated as w, the variable x is the input, and b represents the bias vector [32].

In the proposed MLP algorithm, the output of the previous layer is the input to the next layer. Such that the layers of the MLP of fully connected layers in the network. Thus, each unit functions of the layer are always connected to all other layers' unit function in the neural network. Each layer's unit functions (i.e., weights and other sets of parameters) are independent of the other layer's unit functions. It means the weights of each layer's unit functions are unique. Further, the MLP network defines the loss function, which can measure the performance (sodium prediction) of the proposed MLP classification technique. When the loss function has a high value, the MLP doesn't make an accurate classification or prediction solution to the given problem, and otherwise, it is vice versa [31, 32].

Fig.1 depicts the flow of the proposed MLP based future sodium prediction algorithm. Firstly, one million patients hyponatremia dataset was collected from the hospitals. The outlier and missing data are removed from the hyponatremia dataset using the imputation process. Then the 0.5 million hyponatremia dataset is given to the input layer as the input, and it is trained using the multilayer perceptron algorithm. To obtain a better optimal prediction model, the number of hidden layers is varied from two to twenty by the unit of two. This MLP learning and training process gives the prediction results in the output layer.

The prediction results are evaluated with the error performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Relative Error (MARE), and Root Mean Squared Relative Error RMSRE (RMSRE) are computed for the prediction results [33, 38]. The performance results of the future sodium prediction dataset are analyzed with the precision rate and compared with other existing results.

4. Results Evaluation and Discussion

This section gives detailed results analysis, evaluation of performance metrics, and comparative result analysis. The Anaconda Jupiter notebook and various libarities of scikit-learn have been used to implement the proposed work with an i3 processor, 3 GB RAM system. The taken dataset has been split into 70 %, 15%, and 15% for the training, validation, and testing. To evaluate and validate the performance of the machine learning model, resampling methods are adopted. This method estimates the prediction ability of the machine learning algorithm on new unseen input data. In this work, the 'k' value is chosen as 10; therefore, it can be called a 10-fold cross-validation

Table.2 Performance Error Metrics resulted by MLP

Metrics/Neurons	MSE	RMSE	MAE	MARE	RMSRE
2	0.052	0.2281	0.1521	0.0418	0.073
4	0.1012	0.3181	0.2791	0.071	0.0919
6	**0.0227**	**0.1505**	**0.0691**	**0.0196**	**0.0441**
8	0.0942	0.3069	0.273	0.07	0.0898
10	0.0563	0.2372	0.1693	0.0492	0.1017
12	0.1092	0.3304	0.2975	0.0752	0.0956
14	0.1014	0.3184	0.2832	0.0728	0.0967
16	0.1018	0.3191	0.2862	0.0727	0.0914
18	0.0806	0.2839	0.248	0.0636	0.0773
20	0.1005	0.317	0.2848	0.0722	0.0894

resampling method. The 10-fold cross-validation method intends to reduce the bias of the prediction model.

4.1 Results of MLP Algorithm

The multilayer perceptron algorithm trains the dataset containing the 0.5 million patients' information such as age (A), gender (G), information about diabetes (D), pneumonia (P), liver-disease (L), malignancy (M), pulmonary (Pu), sepsis (Se), SIADH (S), and sodium level (Na) of the patients during admission to the hospital. To determine the quality dataset for the prediction of the future sodium values, the number of hidden neurons is varied from two to twenty [34, 36]. Table. 2 summarizes the resultant performance error metrics values such as MSE, RMSE, MAE, MARE, and MSRE for the MLP algorithm with several different neurons.

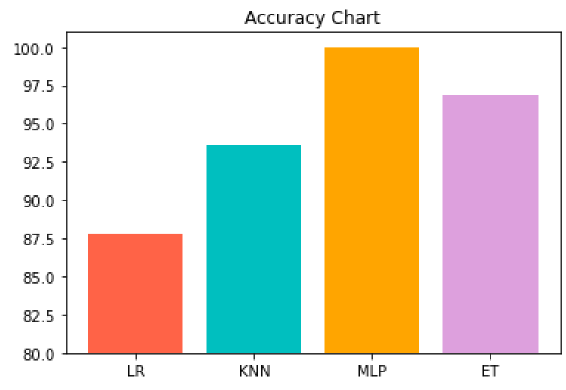

Fig. 2. Comparison of Na+ prediction results by MLP and other classifiers

In Table. 2, the lowest MSE value is highlighted as neuron 6. The error performance metric values for the MSE, RMSE, MAE, MARE, and MSRE for the neuron 6 by MLP algorithm are 0.0227, 0.1505, 0.0691, 0.0196, and 0.0441 respectively; it is the lowest among other neurons. Therefore, the corresponding dataset of neuron 6 is considered the appropriate and optimistic solution for the given hyponatremia patient dataset.

The prediction accuracy, confusion matrix, Mean Square Error (MSE), Kappa, R2 scores of MLP in comparison with logistic regression, K-nearest neighbour, and extra trees algorithms are depicted in in the figures 2, 3, 4, 5, and 6 respectively. The results of the confusion matrix suggest that the MLP has higher true positive rate and true negative rate.

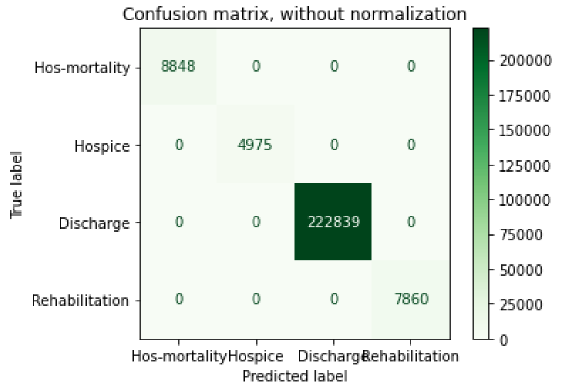

Fig. 3. Confusion matrix of Na+ prediction results by MLP

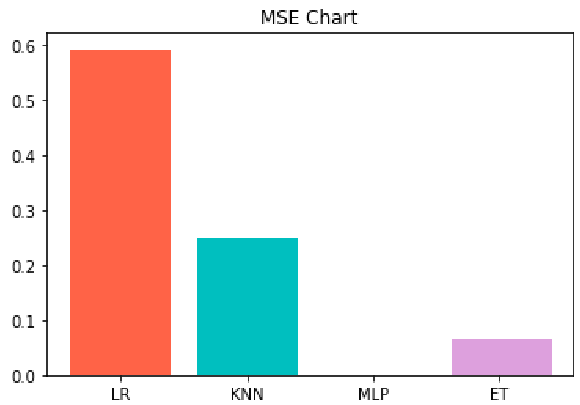

Fig. 4. Comparison of MSE for Na+ prediction results

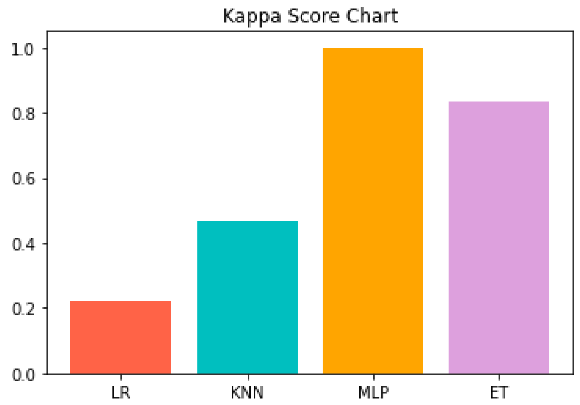

Fig. 5. Comparison of Kappa score for Na+ prediction results

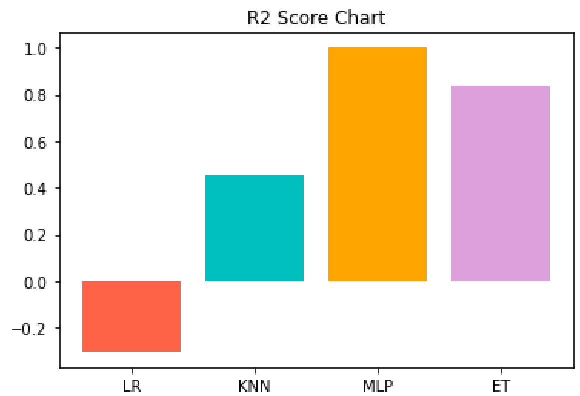

Fig. 6. Comparison of R2 score for Na+ prediction results

5. Conclusion

This work was concentrated on predicting the future sodium range for the patients based on various health history factors such as age, gender, health problems, etc., to predict the hypo/hypernatremia. The proposed MLP algorithm has produced an accurate future serum sodium prediction range than the LR, KNN, and ET algorithms. The LR algorithm has a 41-72 % prediction accuracy rate, whereas the MLP neural network algorithm has an accurate prediction of 91-99 %. The MLP algorithm-based prediction results have 27-50 % improved prediction accuracy than the KNN algorithm-based prediction results. Moreover, the proposed MLP algorithm-based prediction results in 57.1 % of the reduced MSE error rate than the LR, KNN, and ET results in predicting future sodium ranges of patients. The outcome of the proposed MLP algorithm-based future health prediction algorithm could help physicians and patients make further decisions based on their health conditions. The future work will concentrate on forecasting survival rate of the patients after hyponatremia with various health parameters.

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