Finally with the MultiLayerPerceptron, the accuracy level changed with a few parameters being tweaked. Like the other models, initially the training was done with only 500 epochs and a learning rate of 0.3 which made a model less accurate than the tweaked model. The learning rate, alpha then was lowered to 0.1 and the number of epochs were increased to 700. This little change made an increase in the accuracy of the model which was 91.3174% in training period and became 92.1976% in testing period. The slower learning rate and more epochs consolidated the training putting out a more accurate result than the initial one.

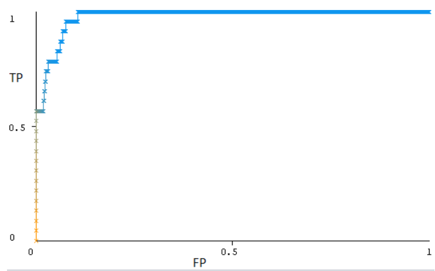

Fig. 5. ROC curve of the class "Very High" of MultiLayerPerceptron

However, after training the model with three different algorithms, the most accurate model was selected which was obviously the one trained with RandomForest algorithm because it presented the highest percentage of accuracy and it also has the lowest RMSE score which is the root mean squared error. Regardless to say, the other models also performed very well as expected. Although RandomForest resulted in the highest accurate model as we can see from table X, all the three models can be used to safely predict the future risks or so to say to forecast the change in sea levels of Bangladesh.

TABLE IX
DATA DIVISION FOR TRAINING AND TESTING

Data	Instances	Percentage
Training	8661	80%
Testing	2166	20%

TABLE X
MODEL VALIDATION

Model	Testing Accuracy	RMSE
RandomForest	93.8596 %	0.152
KNN	91.3204 %	0.177
Neural Network	92.1976 %	0.172

VI. CONCLUSION

Analyzing the results, it is impeccable to say that using random forest we were able to make the best prediction regarding sea-level rise.

Future enhancement of our research may include incorporating more salient features along with more diverse sources of data collection. Different algorithms and approach will be implemented to see the improvement of the model.

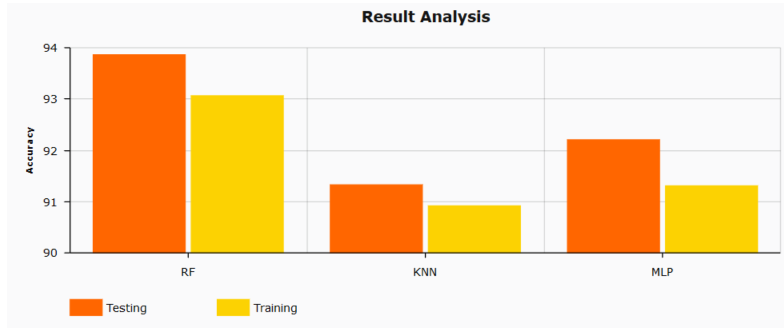

Fig. 6. Result Analysis and Comparison

REFERENCES

[1] Alahmadi, M., Kolmas, J.: Estimating the effect of climate change on global and local sea level rise (2015)

[2] Change, C.: Climate change. Synthesis report (2001)

[3] Das, P.: Prediction model for storm surges in the bay of bengal. Nature **239**(5369), 211 (1972)

[4] Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H.: The weka data mining software: an update. ACM SIGKDD explorations newsletter **11**(1), 10–18 (2009)

[5] Masson-Delmotte, V., Schulz, M., Abe-Ouchi, A., Beer, J., Ganopolski, A., González Rouco, J., Jansen, E., Lambeck, K., Luterbacher, J., Naish, T., et al.: Information from paleoclimate archives (2013)

[6] McKinney, W.: Data structures for statistical computing in python. In: van der Walt, S., Millman, J. (eds.) Proceedings of the 9th Python in Science Conference. pp. 51 – 56 (2010)

[7] Nicholls, R.J., Mimura, N.: Regional issues raised by sea-level rise and their policy implications. Climate research **11**(1), 5–18 (1998)

[8] Rahmstorf, S.: A semi-empirical approach to projecting future sea-level rise. Science **315**(5810), 368–370 (2007)

[9] Warrick, R.A., Barrow, E.M., Wigley, T.M.: Climate and sea level change: observations, projections and implications. Cambridge University Press (1993)

[10] Yin, J., Schlesinger, M.E., Stouffer, R.J.: Model projections of rapid sea-level rise on the northeast coast of the united states. Nature Geoscience **2**(4), 262 (2009)