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MKRF Stacking-Voting: A Data Mining Technique for Predicting Educational Satisfaction Level of Bangladeshis Student During Pandemic

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***Abstract*—Data mining is most efficient when used deliberately to achieve a corporate goal, answer business or research questions, or contribute to a problem-solving solution. Data mining aids in the accurate prediction of outcomes, the recognition of patterns and anomalies, and frequently inform forecasts. Online education is becoming more popular all around the world because of the COVID-19 pandemic. The main goal of this research is to Predict Educational Satisfaction Level of Bangladeshis Students During the Pandemic using data mining approaches by only filling up with some basic questionnaires which are related to the satisfaction level of online education collected through a public survey. By surveying 1004 students from various academic institutions, schools, colleges, and universities on the quality of online education in COVID-19 pandemic scenarios, we were able to determine how productive it would be. Influence how online learning is measured and how satisfied people are with it. To achieve our aim of predicting satisfaction levels, we used a total of eight classifiers, six of which were based classifiers, which we combined with the best three top-scoring classifiers to build a novel ensemble approach called MKRF Stacking and MKRF Voting ensemble classifier. Among those classifiers, the Random Forest classifier outperforms the other six base classifiers with 97.21% accuracy. Our proposed data mining ensemble approaches MKRF Stacking and MKRF Voting outperform applied classifiers. Typically, voting ensemble classifiers outperform voting ensemble classifiers, but in this case, MKRF Stacking defeated MKRF Voting and all applied classifiers with a supreme accuracy of 97.68% (Average). The proposed method would be used in a framework where education counselors find the root causes and minor explanations for dissatisfaction in online education among students so that they can better understand all aspects and provide them with the best advice and solutions to their problems.**

Keywords*— *Education Satisfaction Level, Online Education, Covid-19, Pandemic, Data Mining, MKRF Stacking, MKRF Voting, Bangladesh.

I. INTRODUCTION

This COVID-19 pandemic has crippled the global healthcare system and is threatening everyone's survival. On March 8, 2020, the first three cases of COVID-19 will reach Bangladesh. To prevent the spread of the disease, the Bangladeshi government decided to shut down all communication, including museums, close to all educational institutions, restaurants, offices, markets, and movie theaters, as well as preserve social distance. Close all border crossings and travel between countries. Around 23.1 million students were suspended from class as a result of the COVID-19 incident. Google Meet, Zoom, Ziteboard, Skype, Screencastify, and FaceTime have all been used by several nations' educational institutes to provide regular online instruction to students. To keep general education functioning, the university initially began offering online education, followed by colleges and schools. Now, services such as online teaching and classroom are available through Google Meet, Zoom, and Facebook Live. However, we confront certain challenges on the online education platform, such as restricted internet access, unavailability of electronic equipment, high internet costs, slow internet speeds, and so on [1]. Whether these virtual education platforms can meet the needs of students and teachers, whether network learning is capable of high-quality teaching and learning, whether online education can become an effective medium of special-time education in Bangladesh, and whether Bangladesh's perspective on developing the network online education is based on the research findings.

Now, experts in a variety of nations are attempting to determine how effective online learning approaches are for students. More than one billion children are at danger of falling behind owing to school closures throughout the world, according to UNICEF [2]. In contrast, over 90% of nations have implemented digital remote learning, and over 463 million students have been cut off from the official education system throughout the world [3]. Simultaneously, the epidemic has caused abrupt and significant changes in the higher education eco-system. International students were unable to return to their campuses due to severe lockdowns, health and travel restrictions, causing concern about the consequences for higher education internationally. Though teachers and students confront a number of problems when teaching online learning, the good news is that there is no question that holding courses online is a laudable step done by the present administration to decrease the loss of students' academic activities [4]. Students and instructors must be encouraged to complete this work correctly, and it must be seen as a challenge to complete [5]. Students should remember that they'll be the key stakeholders and that they must be self-motivated to take a greater interest in receiving feedback on their digital classes in all of their activities. With the rapid transition away from the classroom in so many regions of the world, some are questioning if online learning adoption would continue post-pandemic, about how such a shift might affect the global education sector. People in every country have continued to conduct their educational systems online since education is a nation's imperative element and backbone. Education must be expanded in order for any country to survive. Students are enrolling in online education platforms to complete their running courses for this reason. If you pursue your education, you will improve yourself, increase the Gross Domestic Product (GDP), and work in a better environment. We wanted to know if the students were pleased with the online class instruction since if you are educated, you teach the next generation, so we decided to find out. And what impact it will have in the future on a student's humanity.

In this approach, the remainder of the paper is in order. The second section of the paper is a review of the literature. The approach for predict the educational satisfaction level of Bangladeshis during pandemic is discussed in Section III. The experimental results are demonstrated and discussed in Section IV. Section V of the document, certainly, brings the whole thing to a conclusion.

II. Literature Review

We looked at some of publications in this section to determine if there was anything missing from prior studies.

Baashar et al. [6] introduced in their paper about the prediction of student performance based on machine learning algorithms by methodically reviewing several research papers. The objective of this deliberate review was to take a gander at the current Machine learning methods and qualities that are utilized to foresee understudy performance. A few internets based data sets were utilized to play out a precise pursuit of information driven investigations in this review paper. From 1067 database search and after three supreme methods they finally concluded with 30 studies for reviewing and analyzing the method of finding students' performance. Chosen articles uncovered five principal prediction techniques: ANN, DT, SVM, KNN and NB. From their analyzing and reviewing, it was predicted that ANN (Artificial Neural Network) gave the highest accuracy with 98.3% among all the methods.

Hamdan et al. [7] proposed a paper with the students' satisfaction on higher education in Bangladesh from the perspective of public and private university students. The review utilized a quantitative methodology research plan and an example of 182 understudies from different private and public universities in Bangladesh was taken to research. The exceptionality of this review is to utilize binary-logistic-regression techniques to recognize the main segment determinants regarding fulfillment. The review attempted to perceive the general significance of the various determinants that added to the general fulfillment to fabricate climate understudies in both private and public universities in Bangladesh. It likewise distinguished the impacts of demographic backgrounds on understudies' satisfactions. The satisfaction level contrasts as far as public and private associations in that paper and female understudies are less gratified com-pared with their male partner.

Mahonta et al. [8] were intended to experiment about the satisfaction of students regarding the proficiency of services or norm in higher-secondary and higher education in Bangladesh. Total 22 sets of questionnaires were made for the survey with the assistance of the SERVQUAL model or RATER and about 250 students participated from the college to cooperate for their experiment. The investigation discovered that the higher-secondary and advanced education foundations didn't meet the understudies' assumption. In five components of administration quality, a crack was seen between the understudies' assumption and insight. The whole investigation between administration assumption and insight showed that all scores for discernment were lower than their assumption scores.

Waters and Bortree [9] presented in their paper concerning the effect of new media on out of class correspondence in public relations education. The reason for this review is to investigate how new media channels may be utilized to empower out-of-class correspondence between the advertising understudies as well as educators and explicitly to inspect whether uncertain understudies may lean toward these new channels to existing channels. Around 361 students participated in the experiment and about 74% completed the survey. The investigation discovered that new media correspondence channels didn't fundamentally affect the manner in which troubled understudies connected with teachers outside the classroom. While understudies with more elevated levels of correspondence fear are more averse to take part in up close and personal OOC correspondence with educators. The use of data mining in the field of education has increased dramatically in the age of computational intelligence.

Hussain et al. [10] drove a deep learning approach to explore student academic performance and use regression analysis to accurately forecast their outcomes. The dataset was created based on those students who have previously completed their aca-demic activities and contains 10140 records with 9 attributes that have been test-ed from three distinct colleges. With the value of k = 3, the deep learning model records a mean absolute score (mean absolute error) of 1.61 and a loss of 4.7. The linear regression model, on the other hand, provides a loss of 6.7 and a (mean absolute error) score of 1.97. On the basis of academic performance, the suggested study investigates whether the deep learning model is superior to the regression model. There is one limitation: it would be more worthwhile if this experiment were conducted on mid-level students so that students' performance could be predicted and improved. Modern science is eager to predict the future based on data and aspects of present events, utilizing machine learning consciousness, and developing numerous algorithms and models.

EI Guabassi et al. [11] offered a research study that assesses and compares the efficacy of several machine learning algorithms for predicting student performance based on educational data. The supervised algorithms ANCOVA, LR, SVR, DT, RF, PLS, and Log-linear Regression are tested using educational data acquired from open-source platforms. Compare and analyze algorithms used to develop a prediction model based on multiple assessment criteria to reach the research study's expected edge. This study discovered that the

TABLE I. ALL FEATURES WITH EXPLANATION, TYPE AND POSSIBLE VALUES

Features	Explanation	Features Type	Possible Values
GTS	Gender Type of Student	Independent	Male (0), Female (1)
AGS	Age Group of Student	Independent	Less than 20 (0), 20-25 (1), 25-30 (2), 30 Above (3)
TEI	Types of Educational Institution	Independent	School (0), College (1), University (2)
SRA	Residential Area of Student	Independent	Village (0), Town (1)
SDL	Divisional Location of Students	Independent	Dhaka (0), Rajshahi (1), Chattgram (2), Sylhet (3), Rangpur (4), Khulna (5), Barishal (6), Mymensingh (7)
PCM	Preferable Class Mode	Independent	Physical (0), Online Class (1)
HMTSIE	How Much Time Spend on Internet for Education	Independent	1 hour (0), 2 Hour (2), 3 Hour (2), 4 Hour or More (3)
TDUOC	Types of Devices Uses for Online Class	Independent	Mobile (0), Tab (1), Laptop (2), Computer (4)
TIC	Type of Internet Connection	Independent	Mobile Data (0), Broadband-WiFi (1)
SEDPPM	Expanses of Data-Package Per Month by Students	Independent	Up to 1024 MB (1), 1-3 GB (2), 3-5GB (3), 5-10GB (4), 10-15GB (5), above 15GB (6)
HMMSOC	How much Money Spend for Online Class	Independent	300-500 BDT (0), 500-1000 BDT (1), Above 1000 BDT (2)
WPUOC	Which Platform Used for Online Class	Independent	Meet (0), Zoom (1), Facebook Live (3)
DOGS	Doing Group Study in Online	Independent	Yes (1), No (0)
SEPO	Solve Educational Problem via Online	Independent	Yes (1), No (0)
HMILOC	How Much Interesting to Learn via Online Class	Independent	Low (0), Medium (1), High (2)
HMLLC	How Much do Learn in the Lab Courses	Independent	Normal (1), Less (0)
HFPPDOC	Have Face Physical Problem During Online Class	Independent	Yes (1), No (0)
TMCDOL	Teachers are More Counselling During Online Class	Independent	Yes (1), No (0)
HGECM	Have Get Enough Course Materials	Independent	Yes (1), No (0)
PJPM	Possible to Judge Proper Merit	Independent	Yes (1), No (0)
LIS	Losing Interest in Study	Independent	No (0), Maybe (1), Yes (2)
HFMPBL	Have Face Mental Problem	Independent	Yes (1), No (0)
HISCOV	How Much Interrupted Study by Covid-19	Independent	Low (0), Medium (1), High (2)
ESL	Education Satisfaction Level	Dependent	Least Satisfied (0), Satisfied (1), Very Satisfied (2)

Log-linear Regression delivers a superior prediction as well as the behavioral elements that influence students' performance, as well as keeping expectations by clustering and employing artificial neural networks in the future.

Bijoy et al. [12] analyzed broadly with COVID19 impact on Bangladeshi people. According to their study, 57.76% people have severe depression. According to their findings, 57.76% of people suffer from clinically significant depressive disorder (MDD). From Hasan et al. [13] 76.96% are suffering mental health problems and problems that are considered depression in a covid scenario, and this has a negative impact on the education sector and other sector. From Hasan et al. [14] illustrating the supervised approach where students are exposed to depression and the overall influence of covid-19 on schooling throughout the pandemic.

Uddin et al. [16] looked into the impact of the system, information, and service quality on eLearning user satisfaction in Bangladeshi higher education from the standpoint of public universities. This research provided a tested model of the Delone and Mclean information system success model (DMISM) with four integrands SYSQ: system quality, INFQ: information quality, SRVQ: service quality, SAT: user satisfaction for determining user satisfaction. On the basis of 417 data points, 44 percent of users were satisfied, with 388 of them assessed using SMART-PLS 3.0. This research can help public universities create an online learning system that will make academic activities run more smoothly and efficiently.

III. PROPOSED METHODOLOGY

The research study follows certain basic stages such as data collecting, preprocessing data, training the model for a specific application, testing the machine, and obtaining findings. As a basis, we proceeded through step-by-step working procedures to perform this research, and the workflow diagram is shown in Fig. 1.

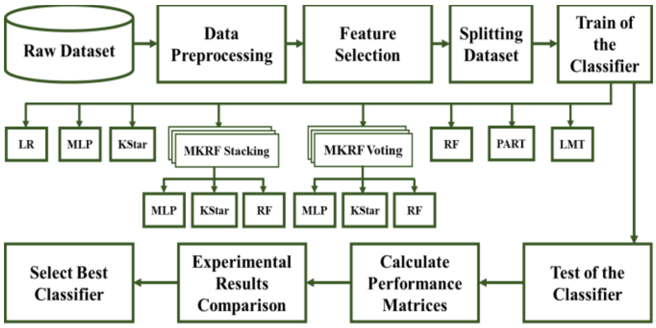

Fig. 1. Step by Step Working Procedure to Predict the Educational Satisfaction Level during Covid-19 Pandemic among the Students of Bangladesh.

A. Dataset Description

We will need a large amount of data to conduct an analysis, which will assist us in training the model to deliver a better outcome. As a result, this study is based on a public survey. We performed a public survey during the epidemic, using a google form with 25 questions. After conducting a public survey, we received 1004 responses from participants. All of the questions are utilized as variables to model attributes and label data. In the beginning, there were 24 independent variables and one variable that acted as label data for the dependent variable. All features, explanation, features types, and possible values are listed in Table I.

B. Data Preprocessing

We need machine-readable data for model feeding, and then we preprocess the data to make it appropriate for training the model. To begin, we eliminate any unnecessary text from our dataset. Then, rather of dealing with lost data from our participants, we deal with missing data. To fill in the gaps in the data, we chose the most common value for categorical data and estimated the mean value for numerical data. Following that, we utilize Label Encoder to convert the category data into a machine-readable numeric number.

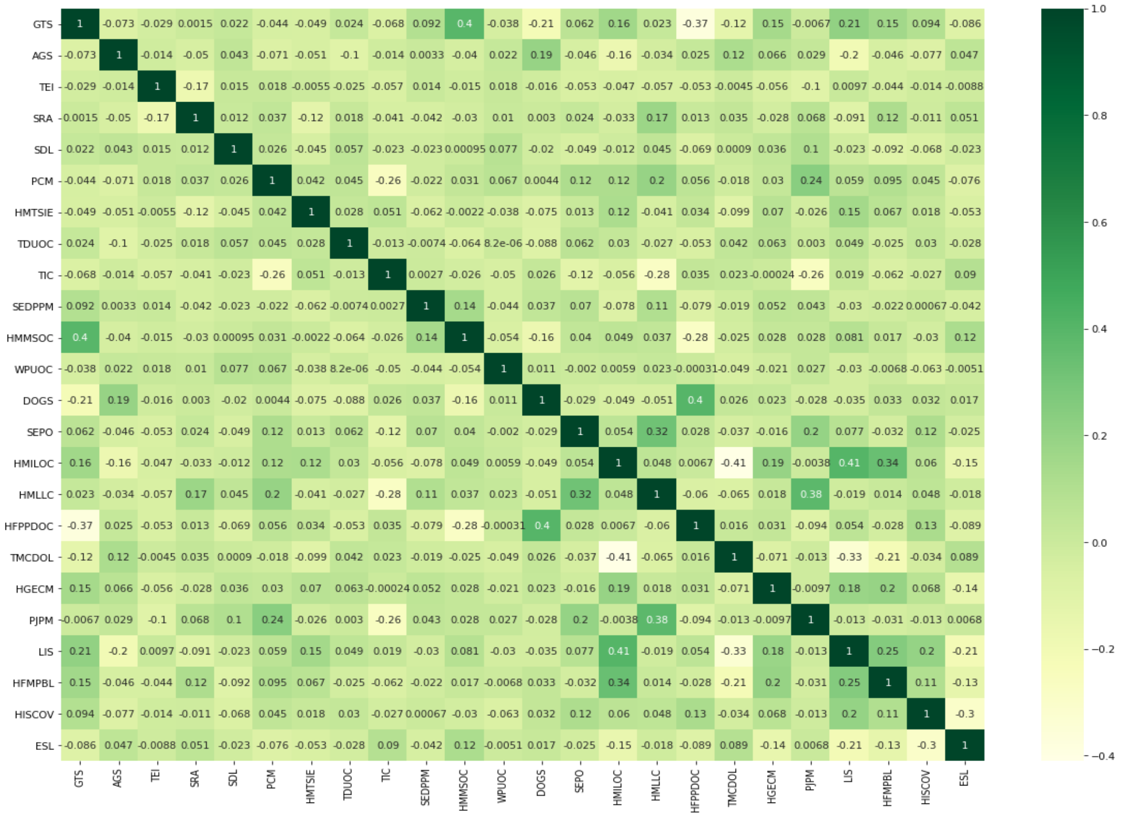

Fig. 2. Correlation Matrix of our Working Dataset.

C. Features Selection

In the physical world, it is infrequent for all of the variables in a dataset to be useful for developing a machine learning model. Including extraneous variables reduces the model's classification performance and may reduce a classifier's overall accuracy. Adding extra variables to a model also increases the model's overall complexity. To identify the top features in our dataset, we examine the correlation matrix and use f_classif feature selection approaches to get the top features for our model implementation. Fig. 2 depicts the correlation between variables in our dataset using the correlation matrix, which is a statistical matrix containing the correlation coefficients for the variables in the dataset.

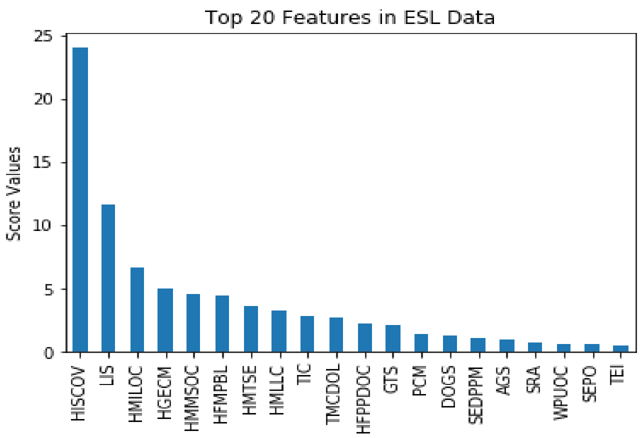

Fig. 3. Top 20 Features in our Working Dataset.

Simultaneously, after using f_classif, we attempt to choose the top 20 features for our model. Then, we compute the score values and choose the top 20 characteristics to go on to the model implementation step. Fig. 3 depicts the top 20 features, along with their rankings.

D. Model Implementation

Following the selection of key features, we divided our dataset into two halves with an 80:20 ratio, which indicates that we utilized 80% of the data to train the model and 20% to test the model. Several classifiers are designed to estimate education satisfaction during a pandemic, and the appropriate model theory is as follows.

The supervised learning approach of logistic regression [16] is used to predict the categorical dependent variable using a collection of the independent variable. The logistic function, which is at the crux of the logistic regression approach. The logistic function, also known as the sigmoid function "(1)", was created by statisticians to characterize the features of population. It's an S-shaped curve that can translate any real-valued number to a value between 0 and 1, but never exactly between those two points.

$$y = \frac{1}{1+e^{-z}} \tag{1}$$

A Multilayer Perceptron (MLP) is a neural network with an input, an output, and one or more hidden layers [17]. A single-layer perceptron can only learn linear functions; however, a multi-layer perceptron can learn both linear and nonlinear functions. MLP's learning method is known as the backpropagation algorithm. The input layer receives the signal, and the output layer predicts a decision based on the input. The hidden layers act as a computational engine to approximate continuous functions. In MLPs, the previous layer's output is utilized as the input to the next layer using the following formula "(2)".

$$y = f\ (WxT + b) \quad (2)$$

The lazy classifier category variant of the KNearest Neighbors (KNN) technique is Instance-Based k (IBK). Instead of creating a model, the IBk technique delivers a just-in-time forecast for a test case. The IBk method uses a distance metric to choose k "near" cases from the training data for each test case, then produces a prediction based on those instances using function “(3)” [18].

KStar is a type of instance-based classifier that uses an entropy-based distance function, making it unique among instance-based classifiers. It's a spin-off of K-Nearest Neighbors (KNN), commonly known as the lazy learner. Instead of learning, this classifier memorizes the training data, conducts some preprocessing, and then waits for the test tuple, which it identifies and classifies based on its likeness to the preset training tuples.

$$\mathrm{Dist}\ (\mathrm{X}, \mathrm{Y}) = \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{D}} (\mathrm{X_i} \mathrm{Y_i})^2} \quad (3)$$

Random Forest [19] is a supervised learning technique, which is a basic machine learning algorithm that, in the majority of cases, produces great results even without hyper-parameter modification. It generates a "forest" out of a group of decision trees that have been trained using “(4)” the "bagging" method. The essential concept of the bagging approach is that mixing several learning models enhances the final result. It is also one of the most often utilized algorithms due to its simplicity and adaptability (it can be used for both classification and regression tasks).

$$\mathrm{RFfi_i} = \frac{\sum_{\mathrm{j}} \mathrm{norm\ fi_{ij}}}{\sum_{\mathrm{j \in all\ features,\ k \in all\ trees}} \mathrm{norm\ fi_{jk}}} \quad (4)$$

The PART (Partial Decision Tree Algorithm) [20] is a rule-based classifier that extracts rules using partial decision trees. It uses the same user-defined parameters as J4.8 and C4.5's heuristics to create the tree. As a result, for a given dataset, J4.8 and the component classifier can both return similar results.

The Logistic Model Tree (LMT) [21] is a tree-based classifier that uses classification trees and logistic regression algorithms. Numeric, nominal, and missing values, as well as binary and multi-class target variables, can all be handled using the LMT method. LMT is a supervised classification approach that combines Logistic Regression with Decision Tree Learning. Using the supervised learning approach of logistic regression, the categorical dependent variable is predicted using a collection of independent factors. A decision tree can be used to graphically and succinctly depict decisions and decision making in decision analysis. The decision tree paradigm is used, as the name implies. Cross-validation is used in the basic LMT induction technique to select a number of LogitBoost iterations that do not overfit the training data.

Staking or Stacked generalization is an ensemble learning technique which using meta classifier in machine learning. Stacking uses the meta-classifier (level-1 classifier) idea to aggregate the separate outputs of the basic classifiers (level-0 classifiers). Though any classifier might very well be used as a level-1 classifier, so in our proposed stacking method we chose the RF as a meta classifier, and MLP, KStar, and RF were our three good scoring base classifiers to get the final ensemble method as MKRF Stacking. To avoid over-fitting, we employed Cross-validation to create the level-1 classifier mode which is highly recommended. In our proposed MKRF Stacking, MPL generates 19 sigmoid nodes, KStar = 1Star (K=1) used the 1 nearest neighbors’ classification, bagging with 100 iterations used in RF and meta-RF. The graphical presentation of MIRF Stacking is shown in Fig. 4.

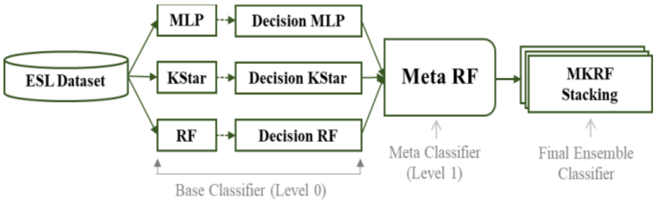

Fig. 4. Classifier Ensemble using MIRF Stacking (MLP, IBK, RF, meta-RF).

Voting classifier is a machine learning technique where the model train on multi ensemble models and generate the prediction using combines the highest probability distributions of these base learners as per chosen output classes. In our proposed MKRF Voting, we conduct the majority voting methods using the maximum probability combination rule. In our proposed MKRF Voting, MPL generates 19 sigmoid nodes, KStar = 1Star (K=1) used the 1 nearest neighbors’ classification, bagging with 100 iterations used in RF. The graphical presentation of MKRF Voting is showed in Fig 5.

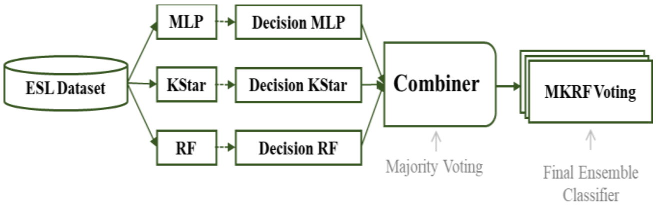

Fig. 5. Classifier Ensemble using MIRF Voting (MLP, IBK, RF).

E. *Calculate Performance Metrics*

After training the classifiers, we analyzed test data to estimate the level of depression among respondents. Here's some of the performance evaluation metrics that were computed. Using these criteria, we found the best classifier to predict in this scenario. Many performance metrics in percent (%) have been calculated using Eqs. “(5–11)” based on the confusion matrix generated by the classifier.

$$Accuracy = \frac{TP + TN}{TP+FN+FP+TN} \times 100\% \quad (5)$$

$$True\ Positive\ Rate\ (TPR) = \frac{TP}{TP+FN} \times 100\% \quad (6)$$

$$True\ Negative\ Rate\ (TNR) = \frac{TN}{FP+TN} \times 100\% \quad (7)$$

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{FP+TN} \times 100\% \quad (8)$$

$$False\ Negative\ Rate\ (FNR) = \frac{FN}{FN+TP} \times 100\% \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (10)$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \times 100\% \quad (11)$$

IV. RESULTS AND DISCUSSIONS

The following section contains a detailed empirical investigation of the classifier ensemble for academic/educational satisfaction level during COVID-19 pandemic. We show that classifier ensembles, which outperform single classifiers in the domain of educational satisfaction detection, are promising approaches for prediction tasks besides our proposed model. In our model implementation section, we applied 8 classification algorithms where 6 classifier was base classifiers, MKRF Stacking and MKRF Voting combine with MLP, KStar, RF classifiers. Least Satisfied (0), Satisfied (1), Very Satisfied (2) are the three classes in our label column; Educational Satisfaction Level (ESL), indicating that our work is a multiclass problem. As a result of the applied classifier, construct a 3×3 confusion matrix as stated in [22], [23]. Table II shows the confusion matrix created by each of the classifiers.

TABLE II. CONFUSION MATRICES FOR APPLIED ALGORITHMS

Model	Class	TP	FN	FP	TN
LR	Least Satisfied	374	144	187	299
	Satisfied	238	190	160	416
	Very Satisfied	22	26	23	933
MLP	Least Satisfied	490	28	31	455
	Satisfied	397	31	40	536
	Very Satisfied	40	18	6	940
KStar	Least Satisfied	498	20	16	470
	Satisfied	408	20	24	552
	Very Satisfied	54	4	4	942
RF	Least Satisfied	502	16	20	466
	Satisfied	406	22	22	554
	Very Satisfied	52	6	2	944
PART	Least Satisfied	443	75	93	393
	Satisfied	334	94	77	499
	Very Satisfied	32	26	25	921
LMT	Least Satisfied	498	20	20	466
	Satisfied	406	22	22	554
	Very Satisfied	54	4	4	942
MKRF Stacking	Least Satisfied	505	13	18	468
	Satisfied	412	16	15	561
	Very Satisfied	52	6	2	944
MKRF Voting	Least Satisfied	500	18	14	472
	Satisfied	412	16	24	552
	Very Satisfied	52	6	2	944

Accuracy, TPR, TNR, FPR, FNR, Precision, and F1 Score from the above confusion matrix are computed to determine the best model for our work and to assess this work. Table 3 shows the results of many performances evaluation measures. Overall analysis separated into two parts: evaluation results for eight base classifiers and results for two proposed MKRF Stacking and MKRF Voting techniques. Table III demonstrates that the Random Forest classifier outperforms the other six base classifiers with 97.21% accuracy. The Random Forest classifier's accuracy for the Least Satisfied (0), Satisfied (1), Very Satisfied (2) classifications is 96.41, 95.81, and 99.40%, respectively. The Random Forest classifier's F1 Score for the Least Satisfied (0), Satisfied (1), Very Satisfied (2) classes is 96.54, 94.86 and 92.86% respectively, which is outrageous of all the classifiers. Furthermore, the result of other data in Table 3 corroborates the Random Forest classifier.

After 6 base classifier results evaluation, we compute the same as Accuracy, TPR, TNR, FPR, FNR, Precision, and F1 Score from the above confusion matrix for our proposed two method: MKRF Stacking and MKRF Voting techniques. Evaluation Results present in Table IV.

According to Table IV, our proposed combination ensemble approaches MKRF Stacking and MKRF Voting outperform applied classifiers. Typically, voting ensemble classifiers outperform voting ensemble classifiers, but in this case, MKRF Stacking defeated MKRF Voting and all applied classifiers with a supreme accuracy of 97.68% (Average).

V. CONCLUSION

We gathered student data and conducted an online education platform survey during the COVID-19 pandemic in Bangladesh. Based on our review and analysis of online student data, we noticed that Zoom and Google Meet provide high-quality services and that certain institutions and universities provide live classes to students via Facebook. Students are experiencing difficulties such as being unable to complete assignments, falling behind, and experiencing video delays and frame drops throughout the class. We also found out that majority of students from suburban and city-regions who used Wi-Fi instead of Mobile Data were satisfied. This research will help us in taking more effective action for all institutions in the case of a pandemic in the future. Even so, for an entire country, this will be hugely advantageous and if we can create effective systems or models for online education, it would be a game changer for remote learning.

REFERENCES

[1] Sultana, Tamanna, and Rezwanul Huque Khan. "Investigating University Students' Satisfaction on Online Class: Bangladesh Perspective." *Bangladesh Educational Journal* (2019).

[2] "Education And COVID-19 - UNICEF DATA". 2021. *UNICEF DATA*. https://data.unicef.org/topic/education/covid-19/.

[3] "COVID-19 And School Closures: Are Children Able To Continue Learning - UNICEF DATA". 2021. *UNICEF DATA*. https://data.unicef.org/resources/remote-learning-reachability-factsheet/.

[4] Hossain, Mohammad Emdad, Mohammad Nazmul Hoq, Israth Sultana, Rakibul Islam, and Md Hassan. "Determinants of Students Satisfaction at Higher Educational Institution in Bangladesh: Evidence from Private and Public Universities." (2019).

[5] Taghizadeh, Seyedeh Khadijeh, Syed Abidur Rahman, Davoud Nikbin, Mirza Mohammad Didarul Alam, Lidia Alexa, Choo Ling Suan, and Shirin Taghizadeh. "Factors influencing students' continuance usage intention with online learning during the pandemic: a cross-country analysis." *Behaviour & Information Technology* (2021): 1-20.

[6] Baashar, Yahia, Gamal Alkawsi, Nor'ashikin Ali, Hitham Alhussian, and Hussein T. Bahbouh. "Predicting student's performance using machine learning methods: A systematic literature review." In *2021 International Conference on Computer & Information Sciences (ICCOINS)*, pp. 357-362. IEEE, 2021.

[7] Hamdan, Khaldoun Mohammad, Ahmad M. Al-Bashaireh, Zainab Zahran, Amal Al-Daghestani, AL-Habashneh Samira, and Abeer M. Shaheen. "University students' interaction, Internet self-efficacy, self-regulation and satisfaction with online education during pandemic crises of COVID-19 (SARS-CoV-2)." *International Journal of Educational Management* (2021).

[8] Mahonta, H. C., M. S. H. Sarker, M. M. Rahman, and S. K. Pramanik. "SERVICE STANDARD AND STUDENTS'SATISFACTION: A STUDY ON SETABGANJ DEGREE COLLEGE, BOCHAGANJ, DINAJPUR, BANGLADESH."

[9] Waters, Richard D., and DENISE SEVICK Bortree. "Exploring the impact of new media on out-of-class communication in public relations education." *Teaching Public Relations Research* 80 (2011): 1-4.

[10] Hussain, Sadiq, Silvia Gaftandzhieva, Md Maniruzzaman, Rositsa Doneva, and Zahraa Fadhil Muhsin. "Regression analysis of student academic performance using deep learning." *Education and Information Technologies* 26, no. 1 (2021): 783-798.

[11] El Guabassi, Inssaf, Zakaria Bousalem, Rim Marah, and Aimad Qazdar. "Comparative Analysis of Supervised Machine Learning Algorithms to Build a Predictive Model for Evaluating Students' Performance." (2021): 90-105.

[12] M. H. I. Bijoy, M. Rabbani, M. I. I. Zarif, M. M. Rahman, M. R. Hasan, and T. Bhowmik, "A Stupendous Statistics On The Pandemic Impact On All Sectors Of Bangladesh" presented at *The International Conference on Advances in Multi-Disciplinary Sciences and Engineering Research (ICAMSER-2021)*, Chitkara University, Himachal Pradesh, Jul. 2-3, 2021

[13] M. Hasan, M. H. I. Bijoy and S. A. Akhi, "Refute the Decision of Auto-Promotion and Real Facts of Digital Online Classes During the Pandemic in Bangladesh," *2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI)*, 2020, pp. 1-6, doi: 10.1109/ICATMRI51801.2020.9398326.

[14] M. R. Hasan, M. H. Imam Bijoy, S. A. Khushbu, S. Akter and S. A. Hossain, "Supervised Method Pursued For Overall Impact of Online Class During Lockdown in Bangladesh," *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2021, pp. 1-5, doi: 10.1109/ICCCNT51525.2021.9579827.

[15] Uddin, MD Main, Abhijit Ghosh, and Osama Isaac. "Impact of the system, information, and service quality of online learning on user satisfaction among public universities students in Bangladesh." *International Journal of Management and Human Science (IJMHS)* 3, no. 2 (2019): 1-10

[16] Kleinbaum, David G., and Mitchel Klein. "Introduction to logistic regression." In *Logistic regression*, pp. 1-39. Springer, New York, NY, 2010.

[17] Murtagh, Fionn. "Multilayer perceptrons for classification and regression." *Neurocomputing* 2, no. 5-6 (1991): 183-197.

[18] Ayu, Media Anugerah, Siti Aisyah Ismail, Ahmad Faridi Abdul Matin, and Teddy Mantoro. "A comparison study of classifier algorithms for mobile-phone's accelerometer based activity recognition." *Procedia Engineering* 41 (2012): 224-229.

[19] Liaw, Andy, and Matthew Wiener. "Classification and regression by randomForest." *R news* 2, no. 3 (2002): 18-22.

[20] Pal, Nikhil R., and Lakhmi Jain, eds. *Advanced techniques in data mining and knowledge discovery*. Springer, 2005.

[21] Landwehr, Niels, Mark Hall, and Eibe Frank. "Logistic model trees." *Machine learning* 59, no. 1-2 (2005): 161-205.

[22] Bijoy, Md Hasan Imam, Sumiya Alam Akhi, Md Ali Ashraf Nayeem, Md Mahbubur Rahman and Md Jueal Mia. "Prediction of Internet User Satisfaction Levels in Bangladesh Using Data Mining and Analysis of Influential Factors." *Bulletin of Electrical Engineering and Informatics* 11, no. 2 (2022).

[23] A. Pramanik, M. H. I. Bijoy, and M. S. Rahman, "Depression Level Prediction during Covid-19 Pandemic among the People of Bangladesh using Ensemble Technique: MIRF Stacking and MIRF Voting" presented at *The International Conference on 4th Industrial Revolution and Beyond (IC4IR) 2021*, Dhaka, Bangladesh, 10 & 11 Dec 2021.

TABLE III. PERFORMANCE EVALUATION FOR SIX BASE CLASSIFIERS

Model	Class	Accuracy (%)	TPR (%)	FNR (%)	FPR (%)	TNR (%)	Precision (%)	F1 Score (%)
Logistic Regression	Least Satisfied	67.03	72.20	27.80	38.48	61.52	66.67	69.32
	Satisfied	65.14	55.61	44.39	27.78	72.22	59.80	57.63
	Very Satisfied	95.12	45.83	54.17	2.41	97.59	48.89	47.31
Multilayer Perceptron	Least Satisfied	94.12	94.59	5.41	6.38	93.62	94.04	94.32
	Satisfied	92.93	92.76	7.24	6.94	93.05	90.85	91.79
	Very Satisfied	97.61	68.97	31.03	0.63	99.37	86.96	76.92
K-Star	Least Satisfied	96.41	96.14	3.86	3.29	96.71	96.89	96.51
	Satisfied	95.62	95.33	4.67	4.17	95.83	94.44	94.88
	Very Satisfied	99.20	93.10	6.90	0.42	99.57	93.10	93.10
Random Forest	Least Satisfied	96.41	96.14	3.08	4.12	95.88	96.12	96.54
	Satisfied	95.81	94.86	5.14	3.82	96.18	94.86	94.86
	Very Satisfied	99.40	93.10	10.34	0.21	99.79	96.30	92.86
PART	Least Satisfied	83.27	85.52	14.48	19.14	80.86	82.65	84.06
	Satisfied	82.97	78.04	21.96	13.37	86.63	81.27	79.62
	Very Satisfied	94.92	55.17	44.83	2.64	97.36	56.14	55.65
Logistic Model Tree	Least Satisfied	96.02	96.14	3.86	4.12	95.88	96.14	96.14
	Satisfied	95.62	94.86	5.14	3.82	96.18	94.86	94.86
	Very Satisfied	99.20	93.10	6.90	0.42	99.58	93.10	93.10

TABLE IV. PERFORMANCE EVALUATION FOR PROPOSED TECHNIQUES MKRF STACKING & MKRF VOTING

Model	Class	Accuracy (%)	TPR (%)	FNR (%)	FPR (%)	TNR (%)	Precision (%)	F1 Score (%)
MKRF Stacking	Least Satisfied	96.91	97.49	2.51	3.70	96.30	96.56	97.02
	Satisfied	96.91	96.26	3.74	2.60	97.40	96.49	96.37
	Very Satisfied	99.20	89.66	10.34	0.21	99.79	96.30	92.86
MKRF Voting	Least Satisfied	96.81	96.53	3.47	2.88	97.12	97.28	96.90
	Satisfied	96.02	96.26	3.74	4.17	95.83	94.50	95.37
	Very Satisfied	99.20	89.66	10.34	0.22	99.78	96.30	92.86