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Research Article

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Posted Date: November 23rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11265282/v1

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Additional Declarations: No competing interests reported.

Predicting and Analyzing Factors Influencing Breastfeeding Practices in Ethiopia Using Ensemble Machine Learning Algorithms

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Abstract

Background: This explores the prediction of breastfeeding practices in Ethiopia using Ensemble machine learning algorithms. Exclusive breastfeeding is crucial for infant health and well-being, and understanding the factors influencing breastfeeding behaviors is vital for public health interventions. In Ethiopia, approximately one-third of infants are introduced to solid or liquid foods before the recommended six months of exclusive breastfeeding. Research shows that sub-optimal breastfeeding practices contribute to a significant percentage (24.0% - 27.0%) of infant deaths in Ethiopia and extend globally, with two-thirds of child deaths worldwide attributed to inadequate exclusive breastfeeding practices [9]. Therefore, this study aims to predict and identify factors associated with breastfeeding practices among Ethiopian children.

A child who does not get proper breastfeeding has higher risks of health issues and several diseases such as Respiratory Infections, Allergies, Cognitive Development, Chronic Diseases, and sudden infant death syndrome (SIDS). generally, sub-optimal breastfeeding practices contribute to infant morbidity and mortality rates in Ethiopia [2]. Therefore, we need research and interventions to promote and support breastfeeding in our country people.

Methods: We collected data for the research from the Ethiopian Demographic and Health Survey (EDHS). The survey interviewed 23007 women of reproductive age between 15-49. Detailed information was collected on respondents' background characteristics, marriage, maternal demographics, socioeconomic status, health indicators, cultural influences, preceding birth interval (months), succeeding birth interval (months), Education level, etc. The study discusses different types of ensemble learning techniques, such as bagging, boosting, and stacking, including algorithms like the Bagging Meta-Estimator, Random Forest, Gradient Boosting, Ada-boost, K Neighbors Classifier, Logistic Regression, and Cat-boost and using metrics such as accuracy, precision, recalls, and F1-score for performance evaluated.

Results: The Bagging Meta-Estimator Algorithm appears to be the best-performing model, with the highest Cross-Validation Accuracy of (97.30%) and strong overall performance metrics and Random Forest, Gradient Boosting, Ada-boost, K Neighbors Classifier, Logistic Regression, and Cat-boost appears 96.23%, 95.93%, 95%, 95%, 91.89% and 96.25% respectively.

Conclusion: This study highlights the effectiveness of ensemble machine learning algorithms in predicting and analyzing factors affecting breastfeeding practices in Ethiopia. Utilizing a comprehensive dataset from the Ethiopian Demographic and Health Survey (EDHS), various ensemble learning techniques such as bagging, boosting, and stacking were applied to identify the most accurate predictive models. The findings reveal that ensemble methods significantly outperform traditional statistical models and simpler machine learning approaches in terms of prediction accuracy and robustness.

Keywords: **Ensemble machine learning algorithms, Breastfeeding practices, Ethiopia, Prediction, Infant health outcomes, EDHS**

1. Introduction

Breastfeeding is universally recognized as one of the most effective ways to ensure the health and well-being of infants and mothers. It provides all the nutrients and antibodies that a baby needs in the first six months of life, which protects them from several infections and diseases. In Ethiopia, there is limited fresh & clean water and healthcare services, based on the problem breastfeeding plays an important role in a baby's survival and well-being [5].

Exclusive Breastfeeding (EBF) is defined as the infant taking only the mother's breast milk, no other liquids or solids or even water, except oral rehydration solution, or drops/syrups of vitamins, minerals, or medicines [1]. EBF is the safest and healthiest food option for infants for the first six months after birth. The World Health Organization (WHO) recommends all mothers to feed their infant only her milk for the first six months after birth [2]. EBF is recommended because a mother's milk is pure and contains all the nutrients for an infant to attain optimal growth and health [3]. Breast-feeding provides many health benefits to both infants and mothers, such as BF having the backbone of child nutrition, as well as the prevention of child morbidity and mortality. It provides antibodies, and bonding opportunities between mother and child [5] [6] [7].

According to the World Health Organization (WHO), the global target for breastfeeding is 70% but in Ethiopia there is only 58% under six months' babies have proper breastfeeding [8].

A child who does not get proper breastfeeding has higher risks of health issues and several diseases such as Respiratory Infections, Allergies, Cognitive Development, Chronic Diseases, and sudden infant death syndrome (SIDS). The magnitude of the problem is significant, as sub-optimal breastfeeding practices contribute to infant morbidity and mortality rates in Ethiopia [5]. Therefore, we need research and interventions to promote and support breastfeeding in our country people. To design effective public health interventions, we need to understand the breastfeeding behavior and mind setup of our society.

Machine learning techniques offer a promising approach to analyzing complex datasets of breastfeeding behavior and mind setup of our people and predicting breastfeeding outcomes based on a range of factors. We utilize machine learning techniques, specifically ensemble learning algorithms, to anticipate breastfeeding behavior in Ethiopia. We analyze a diverse set of factors, such as maternal demographics, socio-economic status, health indicators, cultural influences, etc., and develop a predictive model that can predict breastfeeding practice in our country.

2. Literature Review

Breastfeeding practices in Ethiopia are critical for infant health, with exclusive breastfeeding (EBF) recommended by the World Health Organization for the first six months. Despite its benefits, EBF rates in Ethiopia remain low, influenced by factors such as cultural beliefs, maternal education, and healthcare access. Previous studies have primarily focused on individual determinants, leading to a need for a comprehensive analysis. Ensemble machine learning techniques, known for their predictive accuracy, can enhance understanding of these complex factors. This study aims to fill the gap by utilizing large datasets and advanced algorithms to identify key influences on breastfeeding practices. The findings will provide valuable insights for policymakers and healthcare professionals.

3. Ensemble Algorithms

Ensemble learning is a machine learning technique that enhances accuracy and resilience in forecasting by merging predictions from multiple models [24] [25]. It aims to mitigate errors or biases that may exist in individual models by leveraging the collective intelligence of ensemble learning. The underlying concept behind ensemble learning is to combine the outputs of diverse models to create a more precise prediction. Among these, the **Bagging Meta-Estimator** enhances stability and accuracy by aggregating predictions from multiple models [8]. **Random Forest**, an ensemble method based on decision trees, excels in handling both numerical and categorical data, making it suitable for diverse features related to breastfeeding. **Gradient Boosting** iteratively improves model performance by focusing on errors from previous iterations, while **Ada-boos**t adapts by giving more weight to misclassified instances. The **K Neighbors Classifier** offers simplicity and effectiveness by classifying based on the majority vote of nearest neighbors. **Logistic Regression** provides a foundational approach for binary classification, analyzing the relationship between independent variables and breastfeeding outcomes. Lastly, **Cat-boost,** designed for categorical features, efficiently handles high-dimensional data, improving predictive accuracy. Collectively, these algorithms offer robust tools for analyzing factors influencing breastfeeding practices in Ethiopia.

4. Methodologies

4.1 Data source

We collected data for the research from the Ethiopian Demographic and Health Survey (EDHS). The EDHS is a nationally representative survey that is carried out on a regular basis to collect data on health-related indicators in Ethiopia, such as breastfeeding behaviors and factors influencing breastfeeding. Demographic and Health Surveys are nationally representative household surveys that provide data for a wide range of monitoring and impact evaluation indicators in the areas of population, health, and nutrition [30]. in this study we used the 2016 Ethiopia Demographic and Health Survey (2016 EDHS). The 2016 Ethiopia Demographic and Health Survey (2016 EDHS) is the fourth survey conducted in Ethiopia in 2000, 2005, and 2011.

4.2 Participants of the current study

The EDHS provides a comprehensive overview of population, maternal, and child health issues in Ethiopia [31]. 8 different sets were used to classify the data in EDHS 2016. Data for this study were obtained from the children's dataset. The survey interviewed 23007 women of reproductive age (age between 15-49). Detailed information was collected on respondents' background characteristics, marriage, maternal demographics, socio-economic status, health indicators, cultural influences, preceding birth interval (month), succeeding birth interval (months), Education level, etc.

4.3 Exclusion and inclusion criteria

Mothers with children aged six months or less in the dataset were included as the study population. Independent Variables that are significantly absent from the records' values, Offspring who did not reside with their mother, and unrelated independent variables to breastfeeding practice were excluded from the study.

4.4 Study variables

4.4.1 Outcome/ dependent / variable

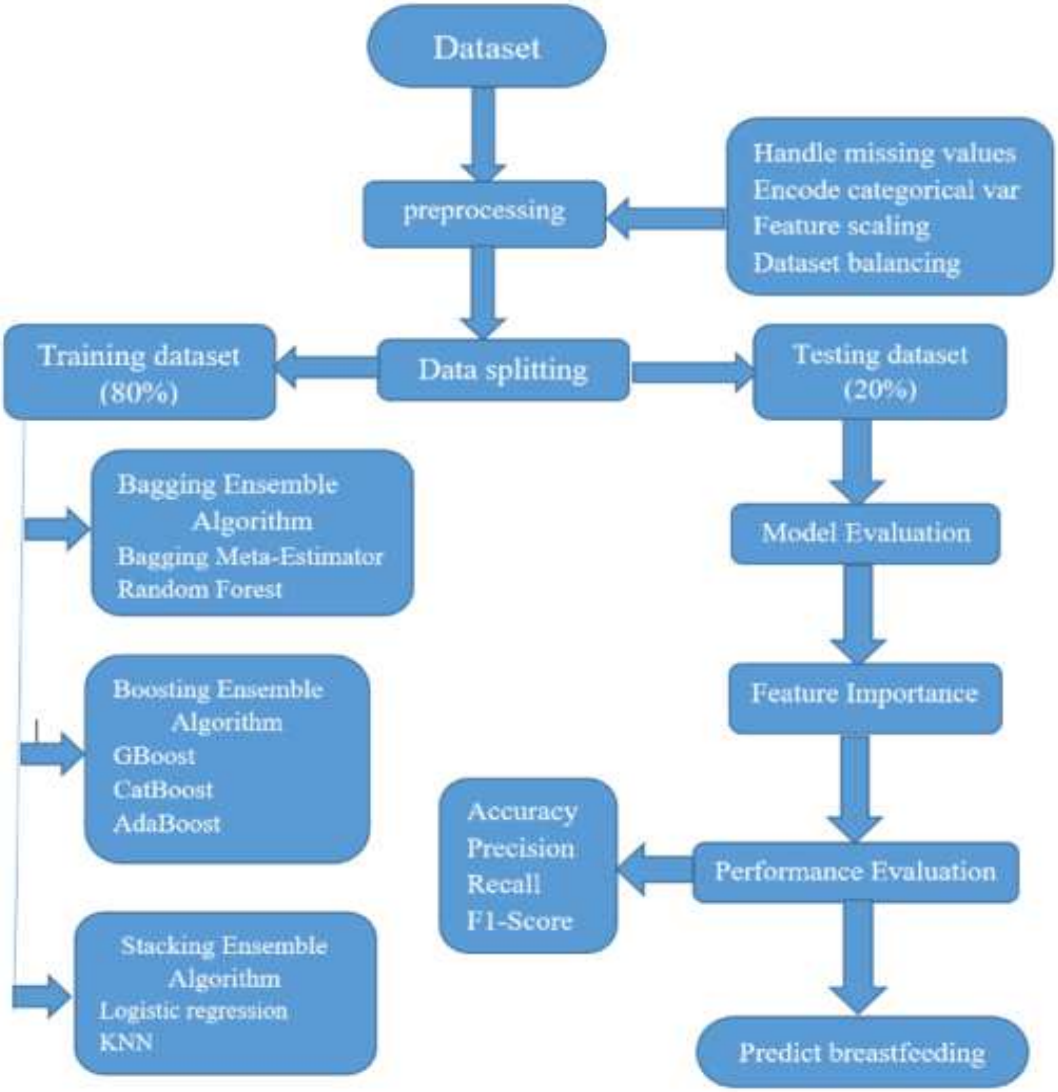
The outcome variable is EBF practice which is a dichotomous variable categorized as 1 (yes) if given child anything other than breast milk except syrup and medicine apart from breast milk and 0 (no) otherwise.

4.4.2 Independent variables

The selection and categorization of independent variables in this study were based on a literature review and the availability of the variables. The independent variables included in this study were the mother's current age (categorized into 15–24 years, 25–34 years, and 35 years and above), region (categorized into, Tigray, Afar, Amhara, Oromia, Somalia, Benshangul Gummuz, SNNPR, Gambela, Harari, Addis Ababa, dire daw), place of residence (categorized into urban and rural), maternal level of education (categorized into no education, primary, secondary, and higher), source of drinking water (categorized into protect, unprotect, public to, piped in, river/da), mother's religion (categorized into protestant, orthodox, Muslim), mother's current marital status (categorized into married, divorced, and widowed/ separated, no longe), place of delivery (categorized into government, responde and other), number of household members (listed) (categorized into <=5, more than 5), sex of child (categorized into male and female), given child anything other than breast milk (yes and no).

4.5 Data preprocessing

Most of the healthcare datasets contain missing values and impurities that can affect the effectiveness of the data. To improve the quality of data obtained through data processing.



4.5.1 Handling Missing Values

In this investigation, we make methods such as imputation (e.g., mean, median, or regression-based imputation) or deletion of rows or columns with missing values. This method ensures that missing values are appropriately handled to avoid biases in the analysis).

```
Missing values before imputation:
age of mother                                        0
Region                                               0
residence                                            0
Eduaction level                                      0
Religion                                             0
marital status                                       0
place of delivery                                10953
household has: electricity                           0
source of drinking water                             0
number of household members (listed)                 0
daughters at home                                    0
sex of child                                         0
preceding birth interval (months)                 5902
succeeding birth interval (months)                5936
given child anything other than breast milk       8183
dtype: int64

Missing values after imputation:
age of mother                                        0
Region                                               0
residence                                            0
Eduaction level                                      0
Religion                                             0
marital status                                       0
place of delivery                                    0
household has: electricity                           0
source of drinking water                             0
number of household members (listed)                 0
daughters at home                                    0
sex of child                                         0
preceding birth interval (months)                    0
succeeding birth interval (months)                   0
given child anything other than breast milk          0
dtype: int64
```

4.5.2 Encoding Categorical Variables

After handling missing values, we Identify the categorical variables in the dataset and encode them into numerical representations suitable for machine learning algorithms. We used a common technique for encoding categorical variables including one-hot encoding for nominal categorical variables (categories without any meaningful order), use one-hot encoding to create binary columns for each category, 1 means the category exists and 0 means it does not exist.

4.5.3 Dataset Balancing

Dataset balancing is just one of the many techniques used in machine learning to improve model performance. Other important steps include feature engineering, hyperparameter tuning, and model selection. Resolving imbalances in the class distribution of a dataset is known as dataset

balancing. This is a crucial stage in the machine learning process since unbalanced datasets might produce erroneous and biased models. When a class has substantially fewer examples than another, the dataset is said to be imbalanced. In real-world datasets, this can often be a problem because certain classes may be harder or rarer to get data for.

There are various methods for balancing datasets, such as:

Oversampling: This involves duplicating examples from the minority class(es) to increase their representation in the dataset. It can be done using techniques like synthetic data generation (e.g., SMOTE) or simple duplication.

Undersampling: It involves removing examples from the majority class(es) to decrease their representation and balance the dataset. It can be done using random undersampling or more sophisticated methods like Tomek links or Edited Nearest Neighbors.

Hybrid methods: This combines oversampling and undersampling techniques to achieve a better balance. Examples include SMOTE-Tomek and SMOTE-ENN.

Class weighting: This involves assigning higher weights to the minority class(es) during the training process, effectively increasing their importance. This can be done by adjusting the loss function or the class weights directly.

The choice of dataset balancing technique depends on the specific dataset and problem at hand. It's often a good idea to try multiple techniques and compare their performance to find the best approach.

In this study, we use the class weighting mechanism for balancing the dataset.

```
= RESTART: C:\Users\Etsubi\Desktop\asmamaw thesis\code\balance.py
Class distribution before balancing:
given child anything other than breast milk
no     21345
yes     1662
Name: count, dtype: int64
Class distribution after balancing:
given child anything other than breast milk
no     20074
yes     2933
Name: count, dtype: int64
```

4.5.4 Data Splitting (Training and Testing Sets)

Split the reprocessed dataset into training and testing subsets. The training set will be used to train the ensemble machine learning models, while the testing set will be used to evaluate their performance. Use an appropriate splitting ratio, such as 80% for training and 20% for testing.

```
---------------------------------------------------- RESTART: C:/Users/ECSUBI/
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23007 entries, 0 to 23006
Data columns (total 16 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0    id                                       23007 non-null  int64
 1   age of mother                             23007 non-null  int64
 2   Region                                    23007 non-null  object
 3   residence                                 23007 non-null  object
 4   Eduaction level                           23007 non-null  object
 5   Religion                                  23007 non-null  object
 6   marital status                            23007 non-null  object
 7   place of delivery                         23007 non-null  object
 8   household has: electricity                23007 non-null  object
 9   source of drinking water                  23007 non-null  object
 10  number of household members (listed)      23007 non-null  int64
 11  daughters at home                         23007 non-null  int64
 12  sex of child                              23007 non-null  object
 13  preceding birth interval (months)         23007 non-null  int64
 14  succeeding birth interval (months)        23007 non-null  int64
 15  given child anything other than breast milk  23007 non-null  object
dtypes: int64(6), object(10)
memory usage: 2.8+ MB
None
```

```
Training set shape: (18405, 59) (18405,)
Testing set shape: (4602, 59) (4602,)


Random Forest Classifier
          for NO class

Train Accuracy: 1.00
Test Accuracy: 0.96
Train precision: 1.00
Test precision: 0.96
Train recall: 1.00
Test recall: 1.00
Train F1-Score: 1.00
Test F1-Score: 0.98

          for YES class

Train Accuracy: 1.00
Test Accuracy: 0.96
Train precision: 1.00
Test precision: 0.98
Train recall: 1.00
Test recall: 0.73
Train F1-Score: 1.00
Test F1-Score: 0.84
```

The split of the dataset into training and testing sets is a common practice in machine learning, where the model is trained on the training data and then evaluated on the unseen testing data to assess its generalization performance.

The training set has a shape of (18405, 59), indicating that there are 18,405 samples, each with 59 features. The testing set has a shape of (4602, 59), indicating that there are 4,602 samples, each with 59 features.

In this study, we checked many algorithm but only show the best of the others after checked those are random forest algorthim. The random Forest algorithm is a powerful ensemble learning method that combines multiple decision trees to make predictions. This algorithm was chosen for the analysis, as it is well-suited for handling both numerical and categorical features, which are present in the given dataset.

The high training and testing accuracy, precision, and recall values suggest that the Random Forest model has excellent performance in classifying the "no" and "yes" classes.

The performance metrics of both the NO and YES class are as follows.

Based on Accuracy in the NO class train Accuracy = 1.00 and test Accuracy = 0.96 but in the YES class train Accuracy = 1.00 and est Accuracy = 0.96. The accuracy is the same for both classes on both the training and test data.

The Precision of NO class train Precision = 1.00 and test Precision = 0.96 in the other way YES class train Precision = 1.00 and Test Precision = 0.98. The precision is slightly higher for the YES class on the test data.

The Recall result of the NO class train Recall = 1.00 and test Recall = 1.00 but the YES class results are train Recall = 1.00 and test Recall = 0.73. The recall is significantly lower for the YES class on the test data, dropping from 100% on the training data to 73% on the test data.

the F1-Score of the NO class train F1-Score = 1.00 and Test F1-Score = 0.98 and the YES class result are train F1-Score = 1.00, test F1-Score = 0.84. The F1 score is also lower for the YES class on the test data.

The main difference is in the recall and F1-score for the YES class on the test data, which are lower than the NO class. The strong performance of the Random Forest model on both the training and testing data suggests that the model has good generalization capabilities and can be applied to new, unseen data with confidence.

4.6 Correlation Matrix

In this study, we have two correlation matrices based on the dataset such as numerical features and categorical features in the dataset. this correlation matrix provides valuable insights into the relationships between the numerical and categorical variables in the dataset.

The following image shows a correlation matrix that visualizes the relationships between the numerical features in the dataset. The features are listed on both the rows and columns, and the cells in the matrix display the correlation coefficients between each pair of features.

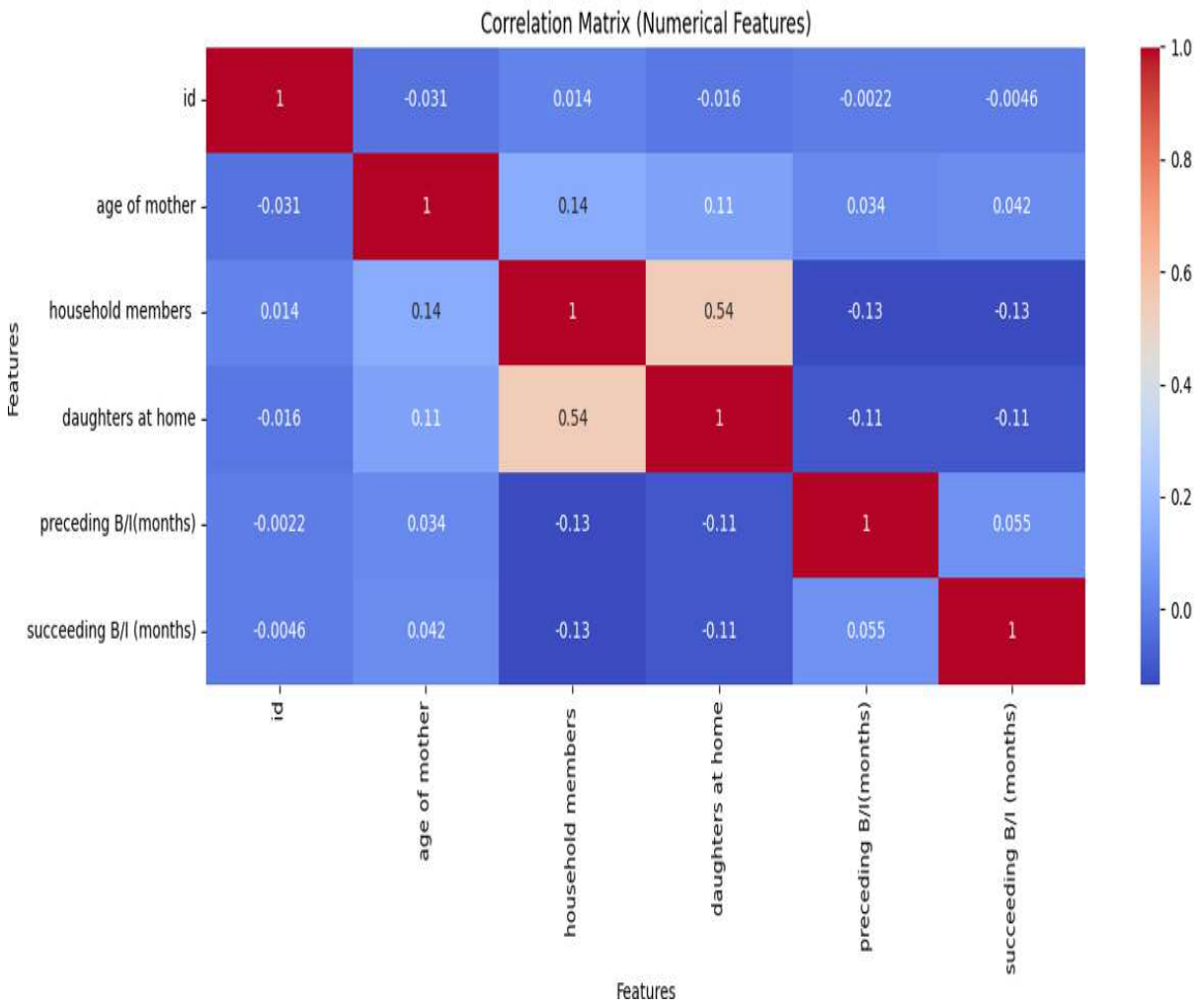


Figure 6:Correlation Matrix for Numerical

The above image displays the correlation matrix for the numerical features in the dataset. The rows and columns represent the different numerical features in the dataset, such as "id", "age of mother", "household members", "daughters at home", "preceding B/I (months)", and "succeeding B/I (months)". The numerical values within the matrix represent the correlation coefficients between the corresponding features. The correlation coefficient ranges from -1 to 1, where -1 indicates a strong negative correlation, 0 indicates no correlation, and 1 indicates a strong positive correlation. For example, the correlation between "id" and "age of mother" is -0.031, indicating a weak negative correlation between these two features. The correlation between "household members" and "daughters at home" is 0.54, indicating a moderate positive correlation. The diagonal elements of the matrix are always 1, as a feature is perfectly correlated with itself.

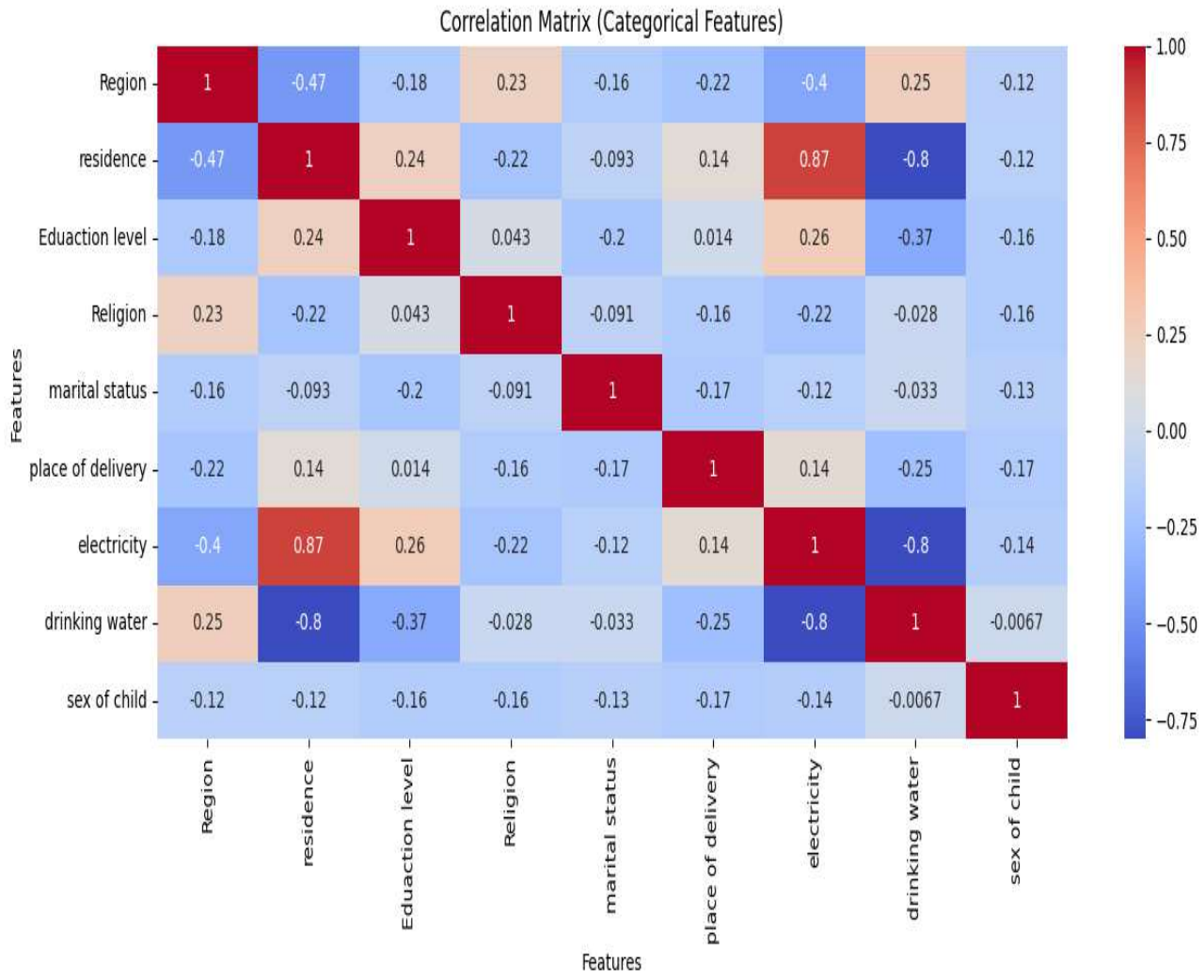


Figure 7: Correlation Matrix for Categorical

The above image correlation matrix helps identify the relationships between the categorical features in the dataset. The rows and columns represent the different categorical features in the dataset, such as "Region", "residence", "Education level", "Religion", "marital status", "place of delivery", "electricity", "drinking water", and "sex of child". The numerical values within the matrix represent the correlation coefficients between the corresponding features. The correlation coefficients range from -1 to 1, where -1 indicates a strong negative correlation, 0 indicates no correlation, and 1 indicates a strong positive correlation.

For example, The correlation between "residence" and "electricity" is 0.87, indicating a strong strong positive relationship. This implies that an individual's place of residence is correlated with their access to electricity and the correlation between "electricity" and "drinking water" is 0.80,

indicating a moderately positive relationship. This suggests that individuals who have access to electricity are also more likely to have access to drinking water.

The correlation between "Region" and "residence" is -0.47, indicating a moderate negative correlation between these two features. This suggests that there may be a relationship between the region and the residence of the individuals in the dataset. The correlation between "marital status" and "place of delivery" is -0.17, indicating a weak negative correlation. This suggests that there may be some relationship between the marital status and the place of delivery of the individuals in the dataset. The correlation between "sex of child" and most other features is very low, ranging from -0.17 to 0.0067. This suggests that the sex of a child has little correlation with the remaining categorical variables in the dataset.

4.7 Model Selection and Configuration

The model selection process involves choosing the appropriate ensemble learning algorithms to analyze the complex datasets and make accurate predictions. Bagging Ensemble Learning Algorithms are Bagging meta-estimator and Random Forest. In Boosting Ensemble Learning Algorithms are Gradient Boosting, Categorical Boosting and Adaptive Boosting and in Stacking Ensemble Learning Algorithm individual machine learning algorithms that can be used in a stacking ensemble, but they are not considered stacking ensemble algorithms themselves such as K-Nearest Neighbors (KNN) and Logistic Regression.The model selection process includes evaluating the performance of each algorithm using appropriate evaluation metrics and cross-validation techniques. This ensures that the selected models are effective in capturing the complex relationships within the dataset and providing valuable insights into breastfeeding practices in Ethiopia.

5. Result

```
Bagging Meta-Estimator Algorithm:
Cross-Validation Accuracy: 0.9730

Random Forest Algorithm:
Cross-Validation Accuracy: 0.9623

Gradient Boosting Algorithm:
Cross-Validation Accuracy: 0.9593

AdaBoost Algorithm:
Cross-Validation Accuracy: 0.9515

KNeighbors Classifier Algorithm:
Cross-Validation Accuracy: 0.9558

Logistic Regression Algorithm:
Cross-Validation Accuracy: 0.9189

CatBoost Algorithm:
Cross-Validation Accuracy: 0.9625
```

	Algorithm	Accuracy	Precision	Recall	F1-Score
0	Bagging Meta-Estimator	97.83%	97.83%	97.83%	97.77%
1	Random Forest	96.18%	96.24%	96.18%	95.94%
2	Gradient Boosting	95.46%	95.56%	95.46%	95.10%
3	Adaptive Boosting (AdaBoost)	94.52%	94.63%	94.52%	94.00%
4	KNeighbors Classifier	95.70%	95.57%	95.70%	95.55%
5	Logistic Regression	90.98%	90.22%	90.98%	90.31%
6	Categorical Boosting (CatBoost)	96.52%	96.56%	96.52%	96.34%

The Bagging Meta-Estimator Algorithm appears to be the best-performing model, with the highest Cross-Validation Accuracy of 0.9730 (97.30%) and strong overall performance metrics (Accuracy, Precision, Recall, and F1-Score). This algorithm could be a good starting point for the proposed research, as it seems to have the highest predictive power among the presented models. The Random Forest Algorithm is the third-best performing model, with a Cross-Validation Accuracy of 0.9623 (96.23%), an accuracy of 95.46%, a precision of 95.56%, a recall of 95.45%, and an F1-score of 95.94%. It could also be a suitable algorithm to explore for this research, as ensemble methods like Random Forest are often effective in capturing complex relationships in data. The

Gradient Boosting Algorithm has a Cross-Validation Accuracy of 0.9593 (95.93%), with an accuracy of 97.18%, precision of 96.24%, recall of 97.18%, and an F1-score of 95.10%.and slightly lower performance metrics compared to the top two algorithms. The Ada-boost and the K Neighbors Classifier have similar Cross-Validation Accuracies, around 95%. The Logistic Regression Algorithm has the lowest Cross-Validation Accuracy of 0.9189 (91.89%) among the presented models, suggesting it may not be the best choice for this particular problem. The Cat-boost Algorithm has the second highest Cross-Validation Accuracy of 0.9625 (96.25%), is also a strong performer, close to the Random Forest Algorithm, and could be an additional ensemble method to explore.

6. Evaluation Metrics

6.1 Accuracy, Precision, Recall, F1-Score

1. Accuracy

Accuracy represents the overall proportion of correct predictions made by the model. In the context of this study on predicting and influencing breastfeeding practices in Ethiopia, the accuracy values range from 90.98% to 97.83%, indicating that the ensemble machine learning models were highly effective in accurately classifying the data. The Bagging Meta-Estimator algorithm achieved the highest accuracy of 97.83%, followed by Catboost and Random Forest at 96.52% and 96.18%, respectively. These high accuracy scores suggest that the models were able to capture complex relationships and patterns within the data, allowing them to make reliable predictions.

2. Precision

Precision measures the proportion of true positive predictions out of the total positive predictions made by the model. In other words, it reflects the model's ability to correctly identify positive instances (i.e., correctly predicting breastfeeding practices) without generating too many false positives. The Precision values range from 90.22% to 97.83%, The Bagging Meta-Estimator algorithm achieved the highest precision of 97.83%, indicating that it was the most proficient in correctly identifying positive instances of breastfeeding practices. CatBoost and Random Forest also demonstrated strong precision with values of 96.56% and 96.24%, respectively.

High precision is important in this study as it ensures that the models can reliably identify the factors that influence breastfeeding practices.

3. Recall

Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances that the model correctly identified. In this study, recall represents the model's ability to correctly identify instances of breastfeeding practices.

In this study, Recall values range from 90.98% to 97.83%, ., indicating that they were highly effective in correctly identifying positive instances of breastfeeding practices. The Bagging Meta-Estimator algorithm achieved the highest recall of 97.83%.

4. F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. It ranges from 0 to 1, with 1 representing the best possible performance. The Bagging Meta-Estimator algorithm achieved the highest F1-score of 97.77%, demonstrating an excellent balance between precision and recall. The high F1 scores across the ensemble models indicate their overall effectiveness in accurately predicting and identifying the factors influencing breastfeeding practices in Ethiopia.

In summary, the high accuracy, precision, recall, and F1-scores achieved by the ensemble machine learning algorithms, particularly Bagging Meta-Estimator, CatBoost, and Random Forest, highlight their exceptional performance in predicting and modeling the complex factors that influence breastfeeding practices in Ethiopia. These metrics demonstrate the models' ability to make reliable and comprehensive predictions, which can provide valuable insights and inform interventions aimed at improving breastfeeding practices in the country. The Bagging Meta-Estimator algorithm was able to strike a good balance between these metrics, achieving the highest overall accuracy.

6.2 Cross-validation

This study used the k-fold cross-validation and divided the data into equally sized folds. The model is trained on k-1 folds and evaluated on the remaining fold, and this process is repeated k times, with each fold serving as the evaluation set once. The performance metrics obtained from each fold are then averaged to obtain the final performance estimate.

In this study, the following code, 5-fold cross-validation is used. This is specified by the ‘cv=5’ parameter when calling the ‘cross_val_score’ function. It means that the data is divided into 5 equal folds, and the model is trained and evaluated 5 times, with each fold serving as the validation set once while the remaining folds are used for training. The performance metrics obtained from

each fold are then averaged to provide an estimate of the model's performance.

```
Bagging Meta-Estimator Algorithm:
Cross-Validation Accuracy: 0.9730

Random Forest Algorithm:
Cross-Validation Accuracy: 0.9623

Gradient Boosting Algorithm:
Cross-Validation Accuracy: 0.9593

AdaBoost Algorithm:
Cross-Validation Accuracy: 0.9515

KNeighbors Classifier Algorithm:
Cross-Validation Accuracy: 0.9558

Logistic Regression Algorithm:
Cross-Validation Accuracy: 0.9189

CatBoost Algorithm:
Cross-Validation Accuracy: 0.9625
```

Figure 11: Cross-Validation

Based on the detailed cross-validation results provided,

The Bagging Meta-Estimator Algorithm has the highest Cross-Validation Accuracy of 0.9730 (97.30%) among the presented models. This suggests that the Bagging Meta-Estimator is likely the most effective algorithm for predicting and analyzing factors influencing breastfeeding practices in this study. It should be the primary focus of the study.

The Random Forest Algorithm comes in second, with a Cross-Validation Accuracy of 0.9623 (96.23%). As an ensemble method, Random Forest could provide complementary insights to the Bagging Meta-Estimator and we should also be considered as part of the study.

The Gradient Boosting Algorithm has a Cross-Validation Accuracy of 0.9593 (95.93%), placing it third in terms of performance. While slightly lower than the top two algorithms, Gradient Boosting is another powerful ensemble technique that could contribute to the study by potentially identifying different patterns or relationships in the data.AdaBoost Algorithm and the KNeighbors Classifier Algorithm have similar Cross-Validation accuracy of around 95%.

The Logistic Regression Algorithm has the lowest Cross-Validation Accuracy of 0.9189 (91.89%)

among the presented models. While it may not be the best-performing algorithm for this particular problem, it could still provide valuable insights, as it can capture different relationships compared to the ensemble methods.

The CatBoost Algorithm, with a Cross-Validation Accuracy of 0.9625 (96.25%), is also a strong performer, close to the Random Forest Algorithm. It could be an additional ensemble method worth investigating as part of the study but It's slightly higher than the random forest algorithm.

In summary, the primary focus should be on the Bagging Meta-Estimator Algorithm, as it demonstrates the highest predictive performance. The Random Forest and CatBoost Algorithms should also be considered as complementary ensemble methods to provide a comprehensive analysis of the key factors influencing breastfeeding practices in the Ethiopian context.

6.3 Confusion Matrix

In Machine learning or Deep learning classification problems, a confusion matrix is a performance evaluation metric that displays the actual and predicted class values to illustrate how well the model performed. It is n x n a square matrix, with the actual and predicted classes represented in the rows and columns, respectively.

Table 2: Confusion Matrix Classification

		Predicted	
		no	Yes
Actual	no	TN	FP
	yes	FN	TP

Where,

True Negative (TN): The number of predictions where the classifier correctly predicts the no class as no. False Positive (FP): The number of predictions where the classifier incorrectly predicts the yes class as no. False Negative (FN): The number of predictions where the classifier incorrectly predicts the no class as yes. True Positive (TP): The number of predictions where the classifier correctly predicts the yes class as an yes.

Accuracy

Accuracy in ML and DL for classification problems refers to the percentage of correctly classified instances by a model out of the total instances in the dataset. It is a commonly used metric to assess the performance of classification models. In other words, It is the ratio of correctly classified

instances to the total number of instances. which defined by equation 4.1

$$Accuracy = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) \times 100\% \quad (4.1.3)$$

Precision

It is the ratio of true positive predictions to the total number of positive predictions, indicating the model's ability to correctly identify positive instances. It is the ratio of correctly predicted yes to all the instances predicted as yes. which defined by equation 4.2

$$\text{Precision} = \left(\frac{TP}{TP + FP}\right) \times 100\% \quad (4.2.3)$$

Recall

Recall is a performance metric used in ML and DL classifiers. It measures the ability of a classifier to correctly identify all relevant instances of a particular class. Specifically, recall calculates the ratio of true positive predictions to the sum of true positives and false negatives. which is defined by equation 4.3

$$Recall = \left(\frac{TP}{TP + FN}\right) \times 100\% \quad (4.3.3)$$

F1-measure

F1-measure is another performance metric used in Machine learning and Deep learning classifiers. It is a combination of precision and recall, providing a balanced evaluation of a classifier's performance. In another expression, F1-measure calculates the harmonic mean of precision and recall. which is defined by equation 4.4

$$F1 - measure = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) \times 100\% \quad (4.4.4)$$

- The following figures are the confusion matrix of all selected ensemble machine learning algorithm of this study.

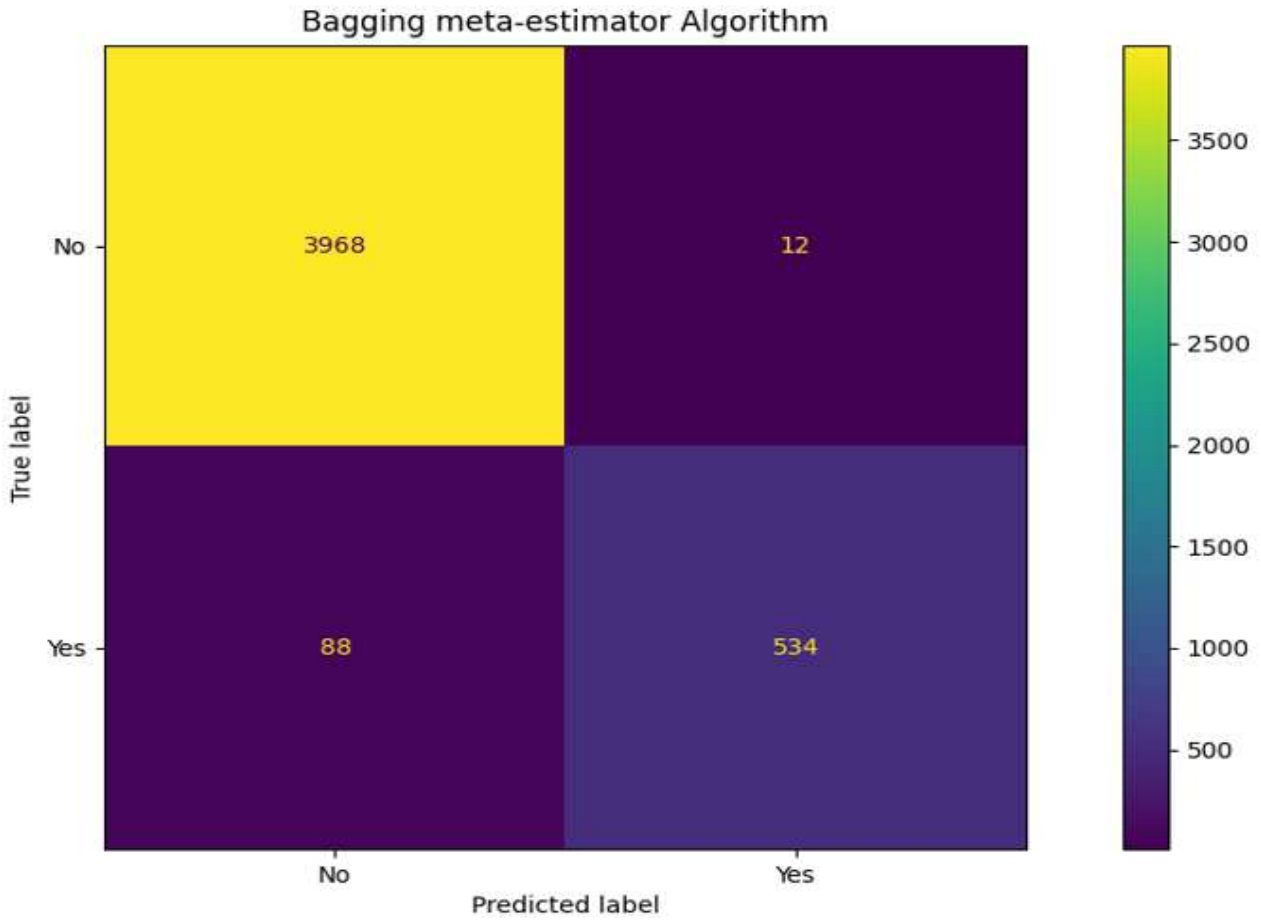


Figure 12: Confusion Matrix for Bagging Meta-Estimator Algorithm

$$Accuracy = \left(\frac{534 + 3968}{534 + 3968 + 12 + 88}\right) \times 100\% = 97.83\% \approx 98\%$$

$$\text{Precision } = \left(\frac{534}{534 + 12}\right) \times 100\% = 97.83\% \approx 98\%$$

$$\text{Recall } = \left(\frac{534}{534 + 88}\right) \times 100\% = 85.85\% \approx 86\%$$

$$\text{F1} - \text{score} = 2 * \left(\frac{97.83 * 85.85}{97.83 + 85.85}\right) \times 100\% = 91.43\% \approx 91\%$$

❖ Generally, the manual calculation result is correct with the displayed output.

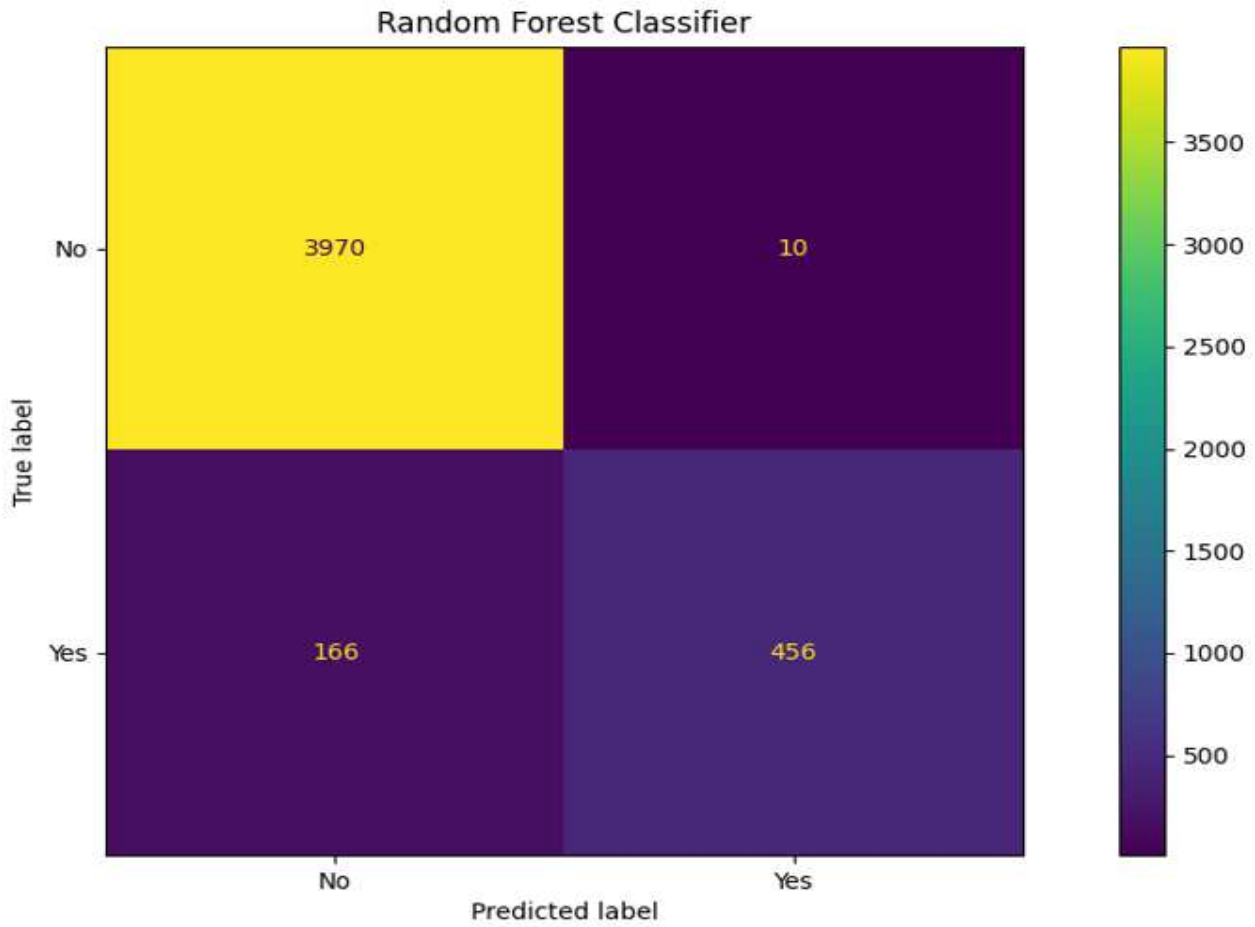


Figure 13: Confusion Matrix for Random Forest Algorithm

$$Accuracy = \left(\frac{456 + 3970}{456 + 3970 + 10 + 166}\right) \times 100\% = 96.21\% \approx 96\%$$

$$\text{Precision } = \left(\frac{456}{456 + 10}\right) \times 100\% = 97.85\% \approx 98\%$$

$$\text{Recall } = \left(\frac{456}{456 + 66}\right) \times 100\% = 73.36\% \approx 73\%$$

$$\text{F1} - \text{score } = 2 * \left(\frac{97.85 * 73.36}{98.85 + 73.36}\right) \times 100\% = 83.36\% \approx 83\%$$

❖ Generally, the manual calculation result is correct with the displayed output.

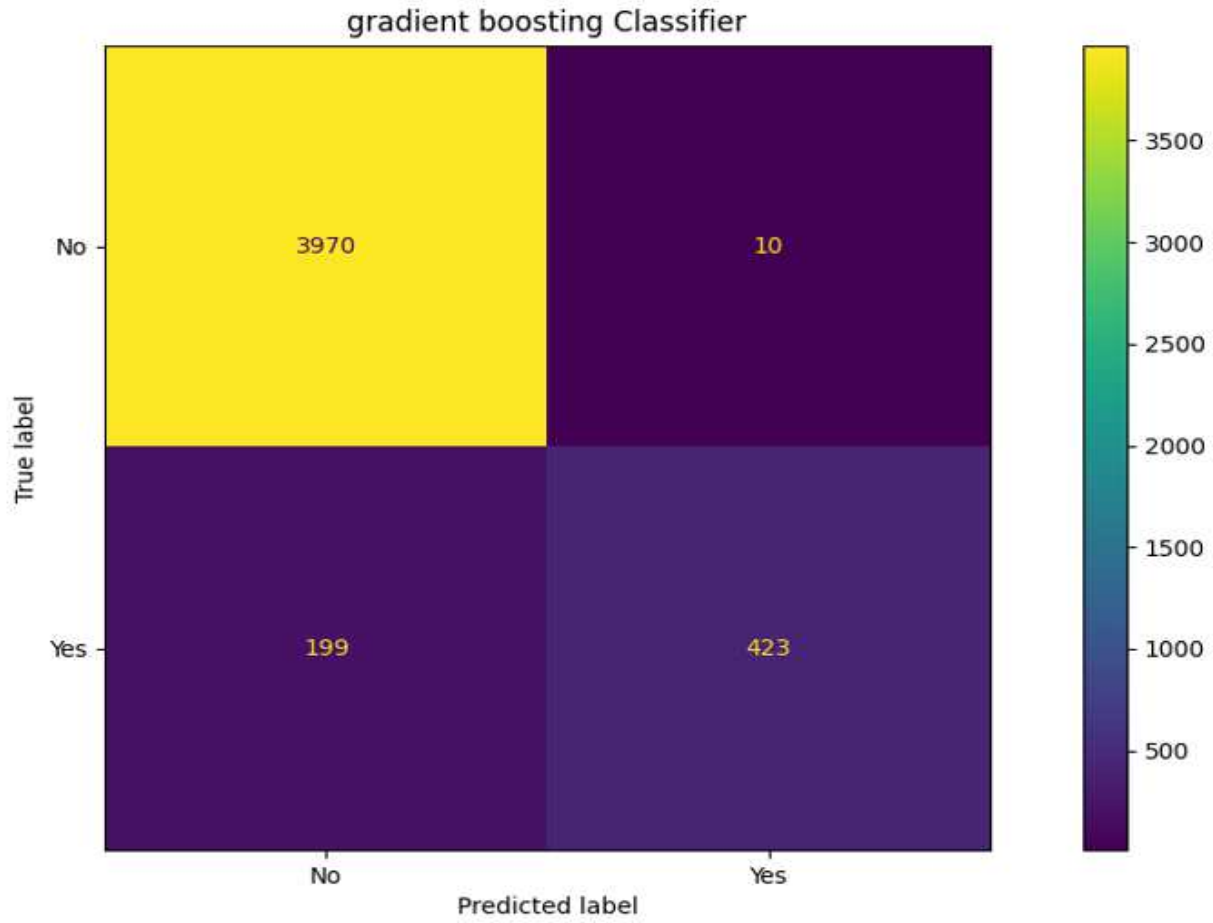


Figure 14: Confusion Matrix for Gradient Boosting Algorithm

$$Accuracy = \left(\frac{423 + 3970}{423 + 3970 + 10 + 199}\right) \times 100\% = 95.46\% \approx 95\%$$

$$\text{Precision } = \left(\frac{423}{423 + 10}\right) \times 100\% = 97.69\% \approx 98\%$$

$$\text{Recall } = \left(\frac{423}{423 + 199}\right) \times 100\% = 68.03\% \approx 68\%$$

$$\text{F1} - \text{score } = 2 * \left(\frac{97.69 * 68.03}{97.69 + 68.03}\right) \times 100\% = 80.01\% \approx 80\%$$

❖ Generally, the manual calculation result is correct with the displayed output.

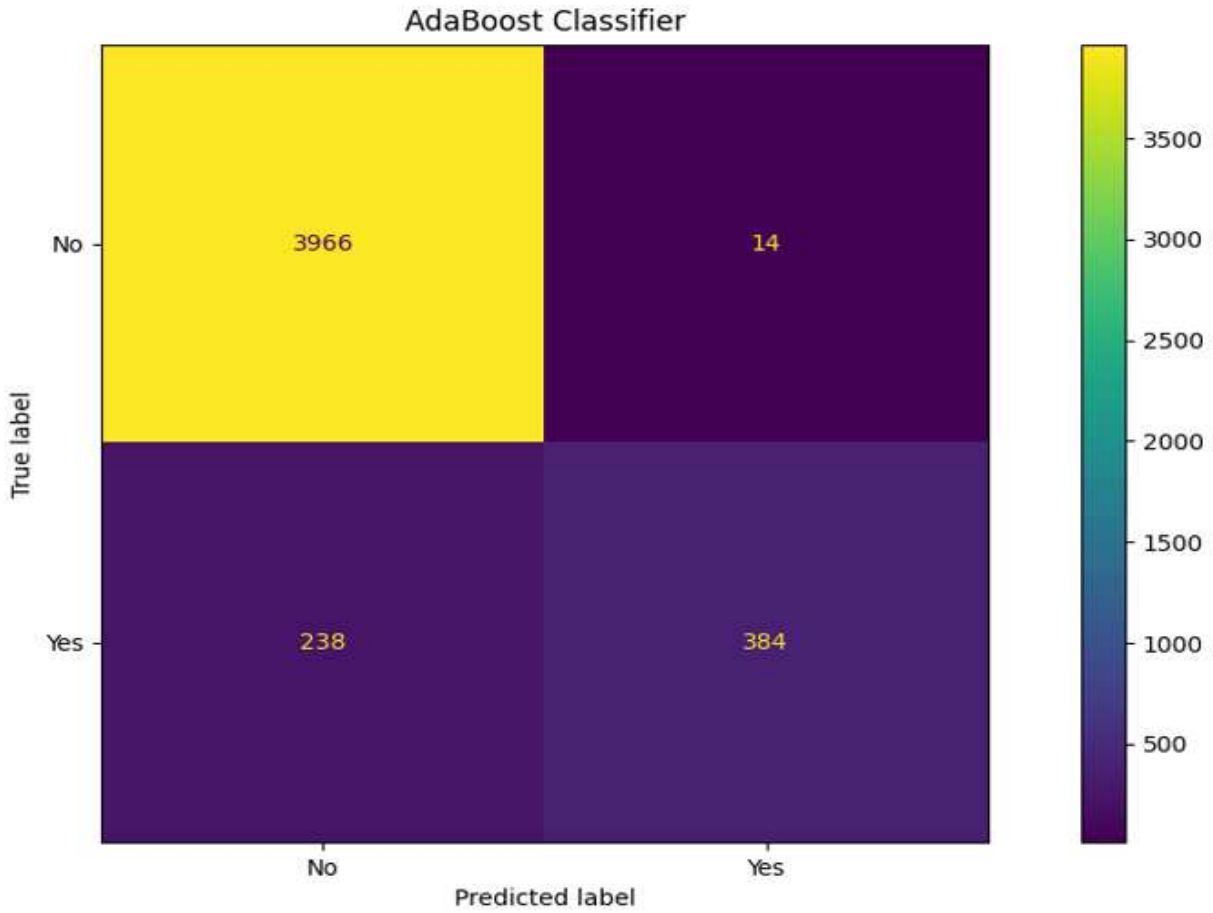


Figure 15: Confusion Matrix for AdaBoost Algorithm

$$Accuracy = \left(\frac{384 + 3966}{384 + 3966 + 14 + 238}\right) \times 100\% = 94.53\% \approx 95\%$$

$$\text{Precision } = \left(\frac{384}{384 + 14}\right) \times 100\% = 96.48\% \approx 97\%$$

$$\text{Recall } = \left(\frac{384}{384 + 238}\right) \times 100\% = 61.77\% \approx 62\%$$

$$\text{F1} - \text{score } = 2 * \left(\frac{96.48 * 61.77}{96.48 + 61.77}\right) \times 100\% = 75.31\% \approx 75\%$$

❖ Generally, the manual calculation result is correct with the displayed output.

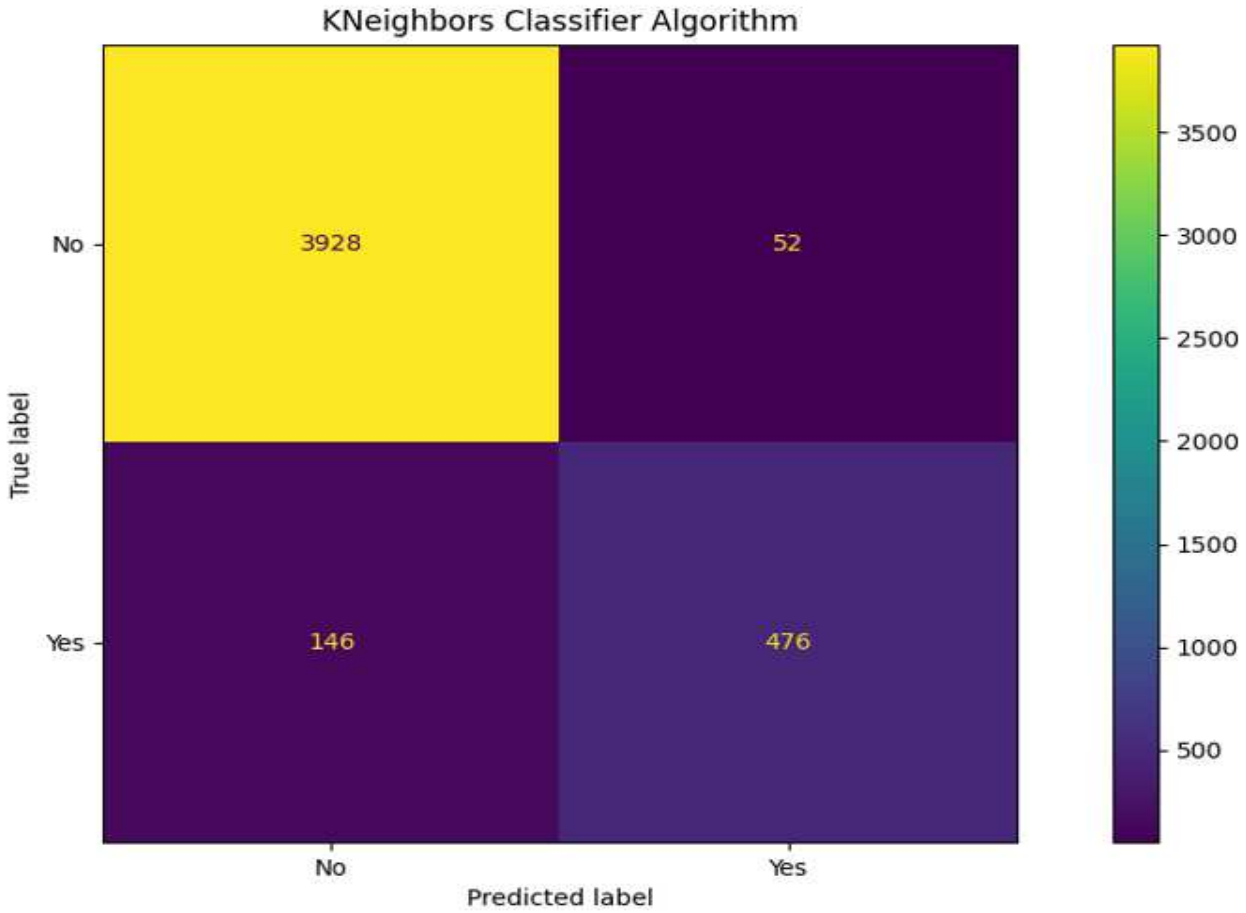


Figure 16: Confusion Matrix for KNieghbors classifier Algorithm

$$Accuracy = \left(\frac{476 + 3928}{476 + 3928 + 52 + 146}\right) \times 100\% = 95.68\% \approx 96\%$$

$$\text{Precision } = \left(\frac{476}{476 + 52}\right) \times 100\% = 90.15\% \approx 90\%$$

$$\text{Recall } = \left(\frac{476}{476 + 146}\right) \times 100\% = 76.53\% \approx 77\%$$

$$\text{F1} - \text{score } = 2 * \left(\frac{90.15 * 76.53}{90.15 + 76.53}\right) \times 100\% = 82.79\% \approx 83\%$$

❖ Generally, the manual calculation result is correct with the displayed output.

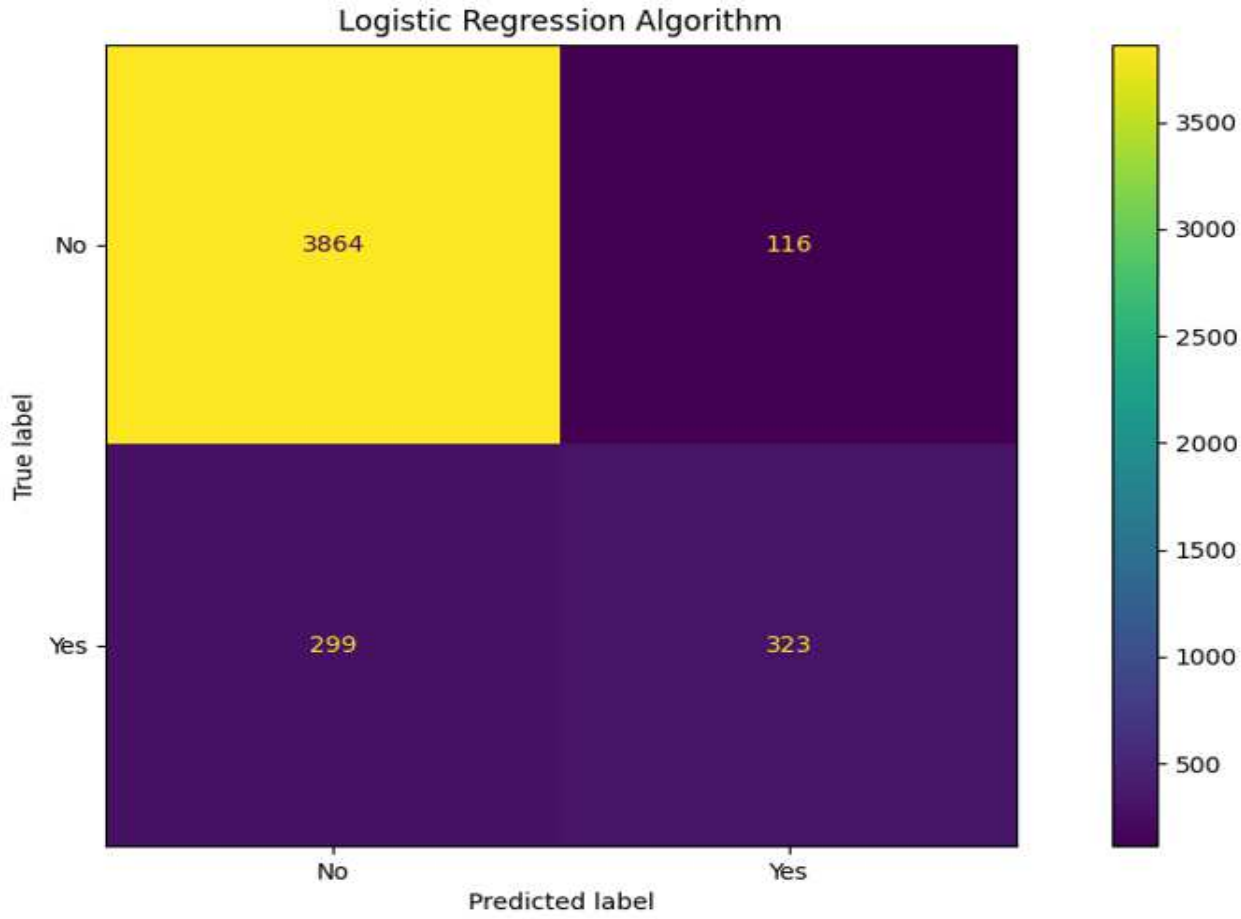


Figure 17: Confusion Matrix for Logistic Regression Algorithm

$$Accuracy = \left(\frac{323 + 3864}{323 + 3864 + 166 + 299}\right) \times 100\% = 91.01\% \approx 91\%$$

$$\text{Precision } = \left(\frac{323}{323 + 166}\right) \times 100\% = 73.58\% \approx 74\%$$

$$\text{Recall } = \left(\frac{323}{323 + 299}\right) \times 100\% = 51.92\% \approx 52\%$$

$$\text{F1} - \text{score } = 2 * \left(\frac{73.58 * 51.92}{73.58 + 51.92}\right) \times 100\% = 60.92\% \approx 61\%$$

❖ Generally, the manual calculation result is correct with the displayed output.

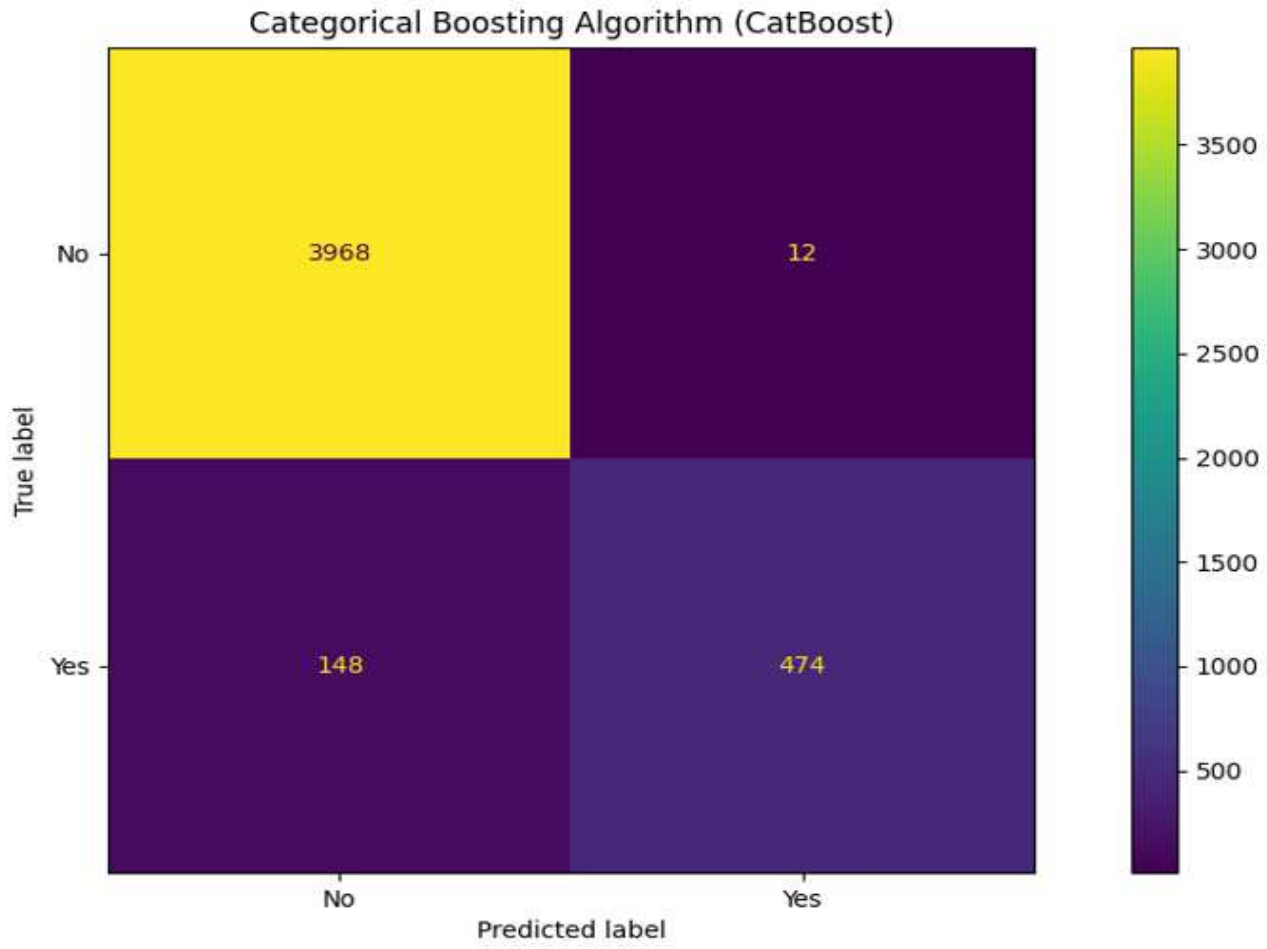


Figure 18: Confusion Matrix for Categorical Boosting Algorithm

$$Accuracy = \left(\frac{474 + 3968}{474 + 3968 + 12 + 148}\right) \times 100\% = 96.52\% \approx 97\%$$

$$\text{Precision } = \left(\frac{474}{474 + 12}\right) \times 100\% = 97.53\% \approx 97\%$$

$$\text{Recall } = \left(\frac{474}{474 + 148}\right) \times 100\% = 76.24\% \approx 76\%$$

$$\text{F1} - \text{score } = 2 * \left(\frac{97.53 * 76.24}{97.53 + 76.24}\right) \times 100\% = 85.62\% \approx 86$$

❖ Generally, the manual calculation result is correct with the displayed output.

6.4 Receiver Operating Characteristic (ROC)

The Receiver Operating Characteristic (ROC) curve is a graphical representation of the performance of a binary (or multi-class) classification model. It is a plot of the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds. It is created by plotting the TPR (y-axis) against the FPR (x-axis) at different classification thresholds. The classification threshold is the probability or score cutoff used to assign an instance to a positive or negative class but the classification threshold is varied, the TPR and FPR change, and the ROC curve is traced out.

TPR (also called Sensitivity or Recall) is the proportion of positive instances that is correctly identified by the model and FPR is the proportion of negative instances that are incorrectly identified as positive.

A perfect classifier would have a ROC curve that passes through the top-left corner (0, 1), indicating a TPR of 1 (no false negatives) and an FPR of 0 (no false positives).

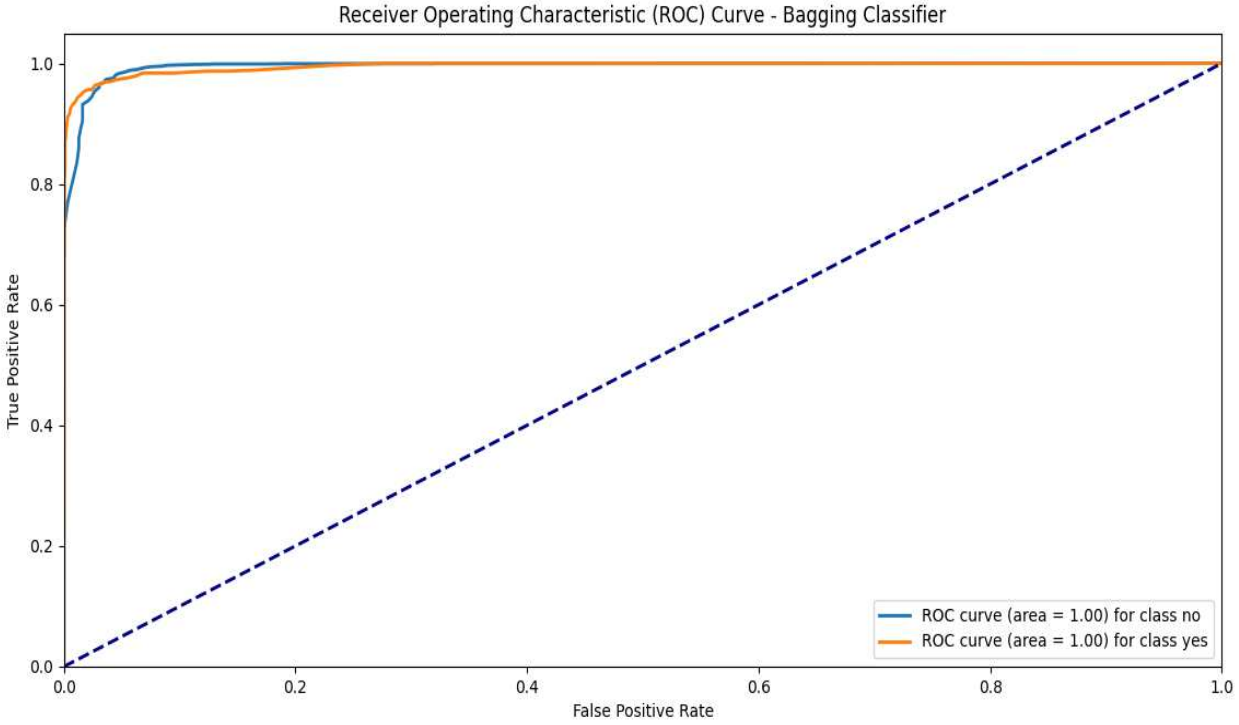


Figure 19: ROC Curve-Bagging

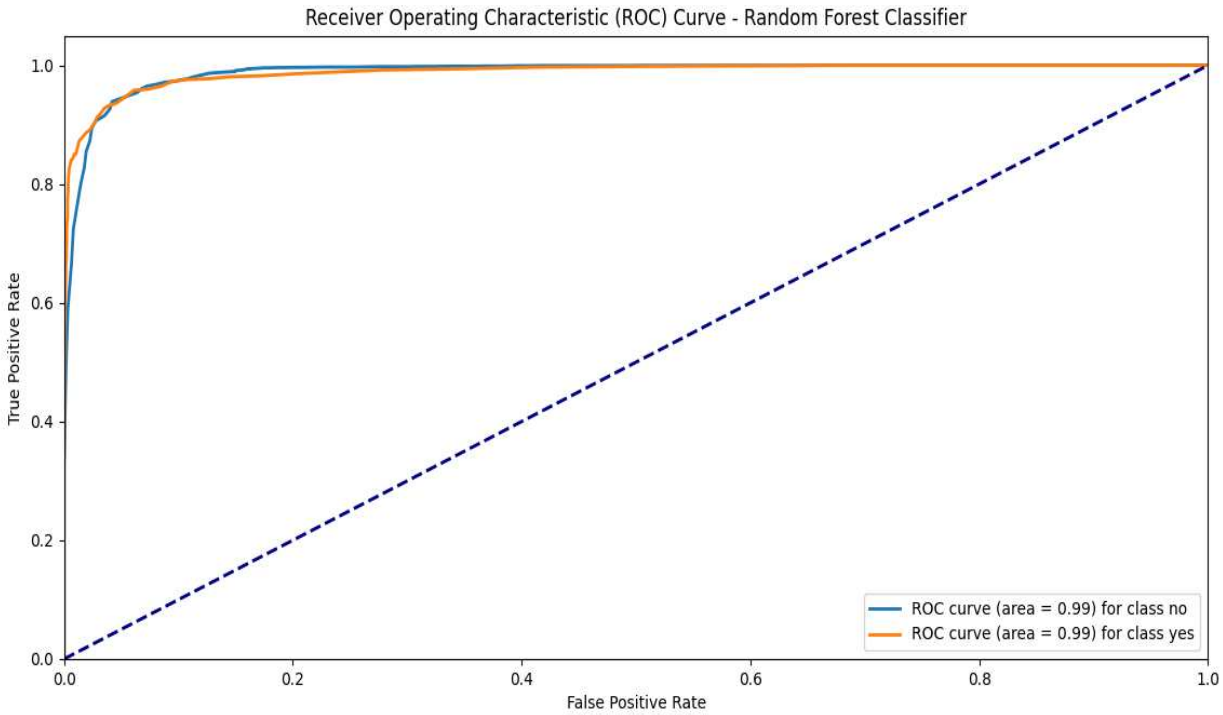


Figure 20: ROC Curve-Random

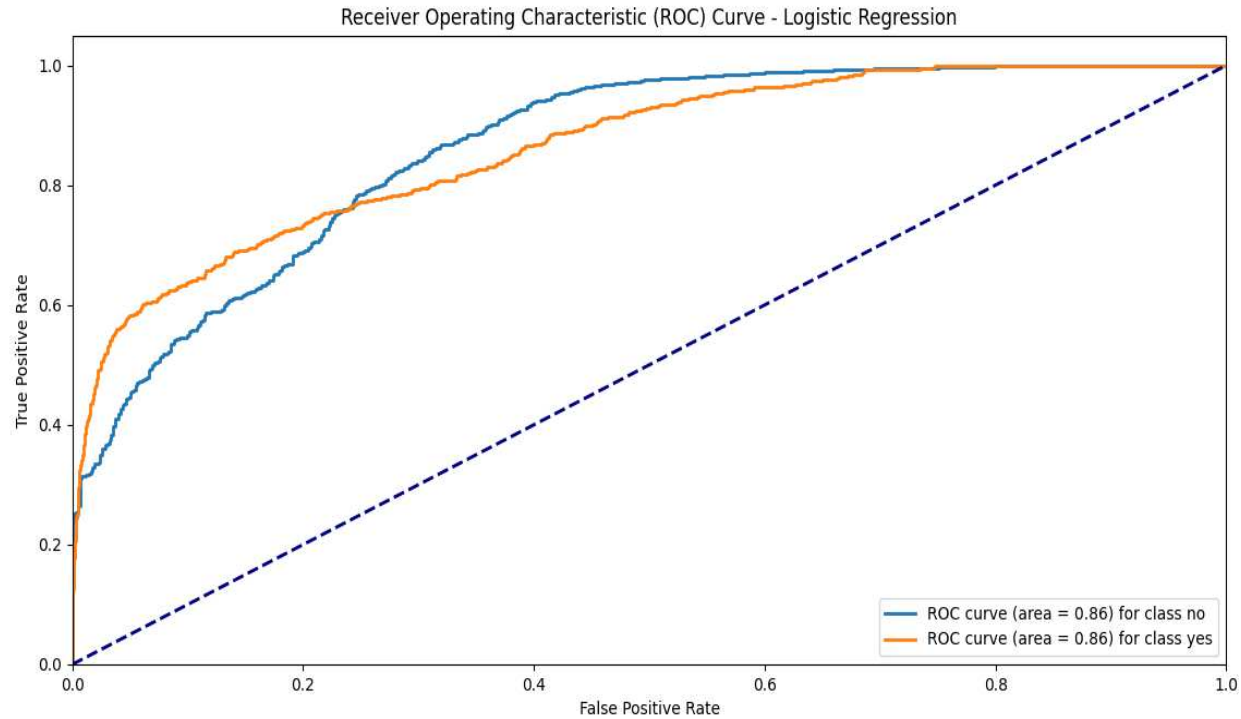


Figure 21: ROC Curve-Logistic Regression

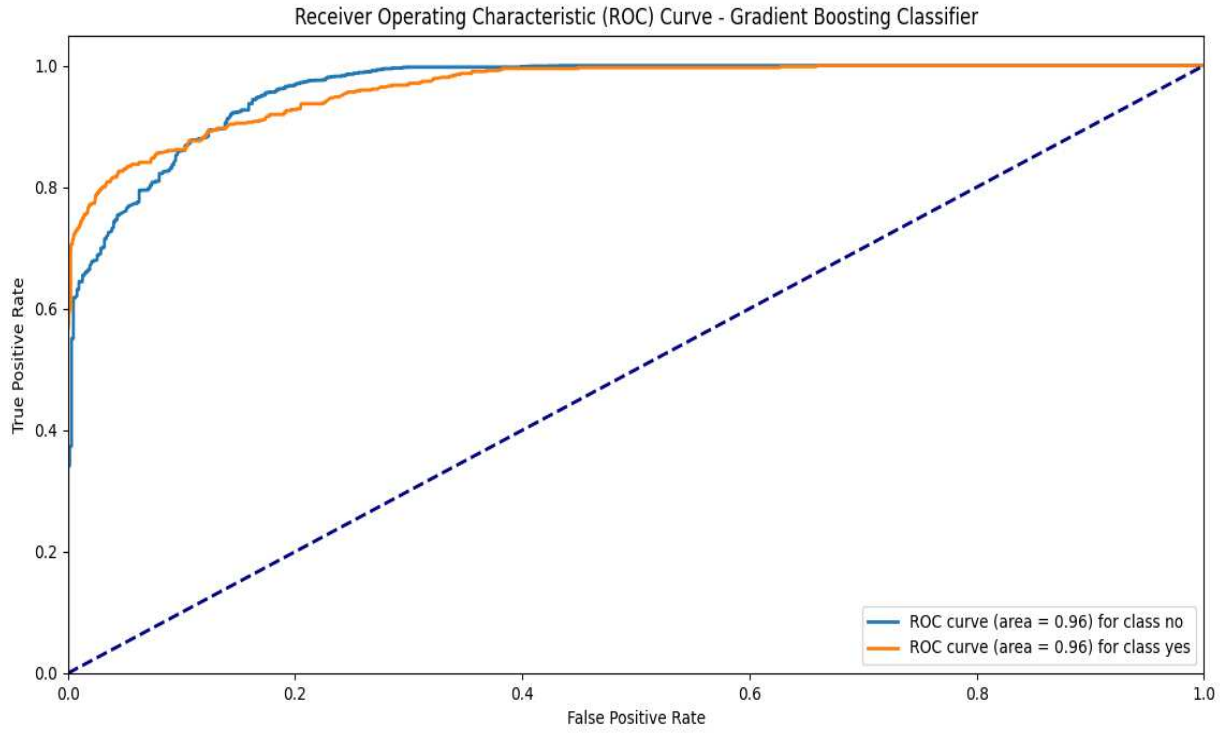


Figure 22: ROC Curve-Gradient Boosting

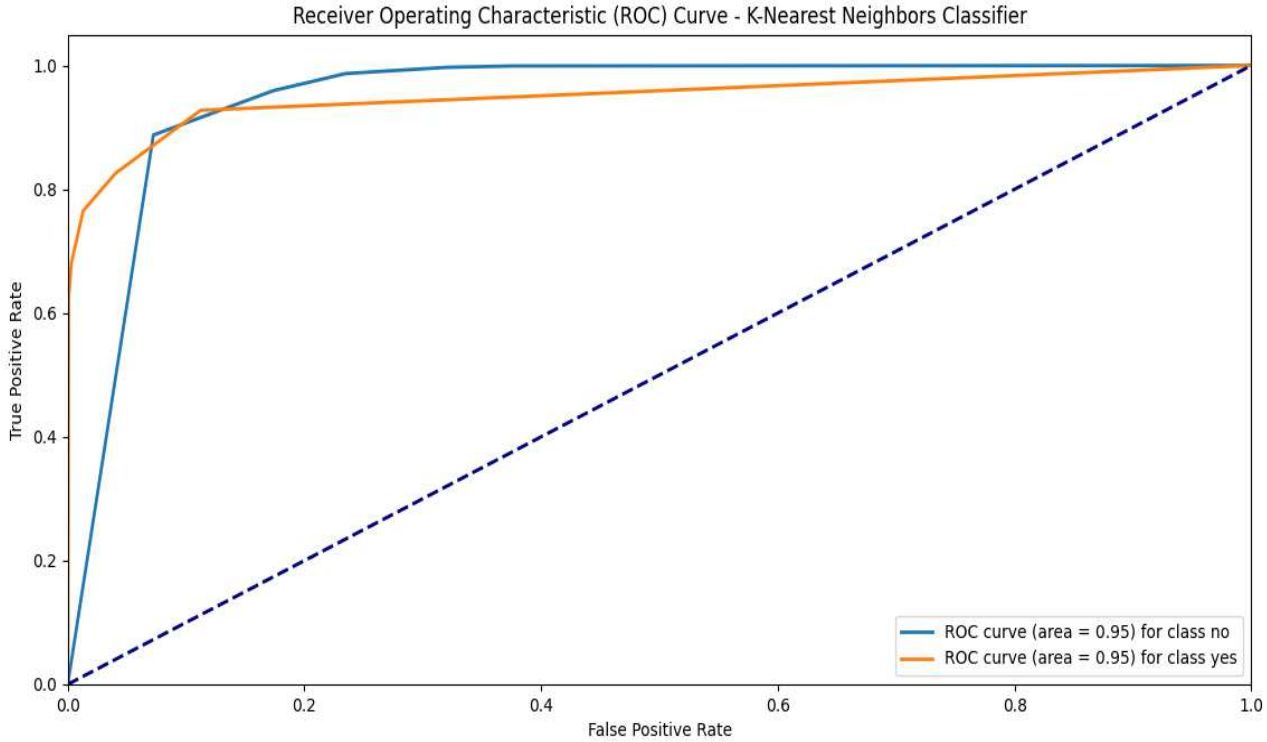


Figure 23: ROC Curve-K-Nearest Neighbors

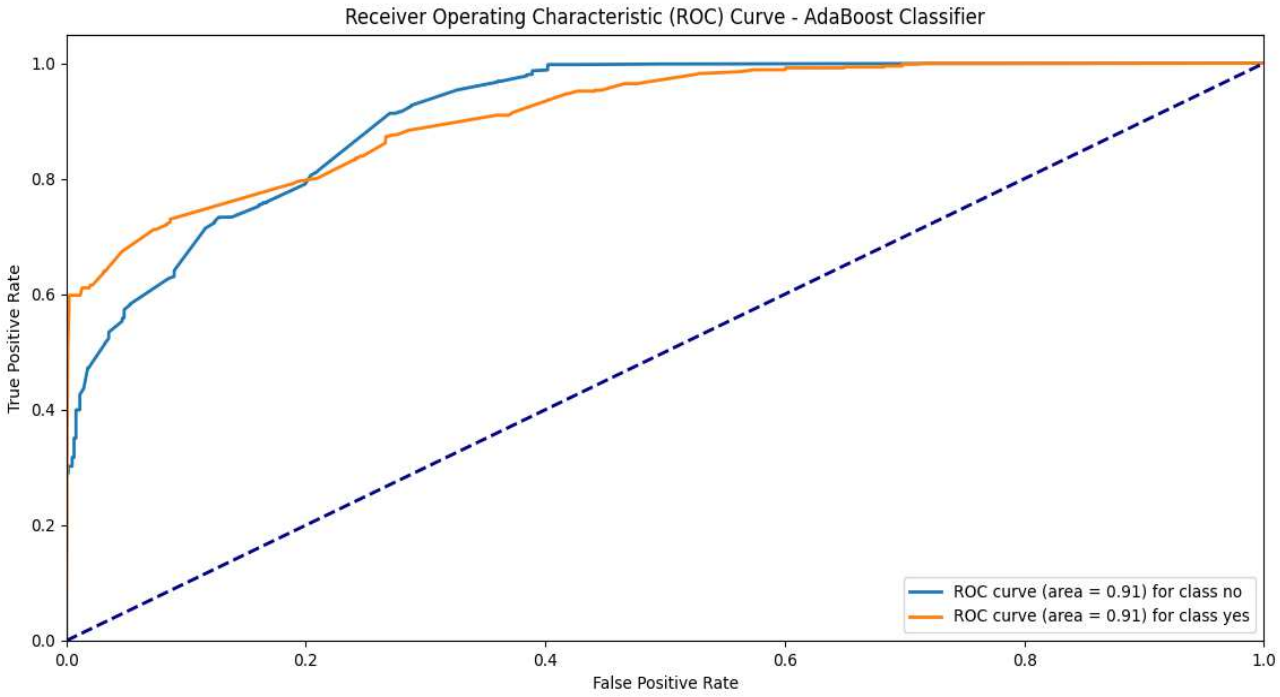


Figure 24: ROC Curve-Adaboost

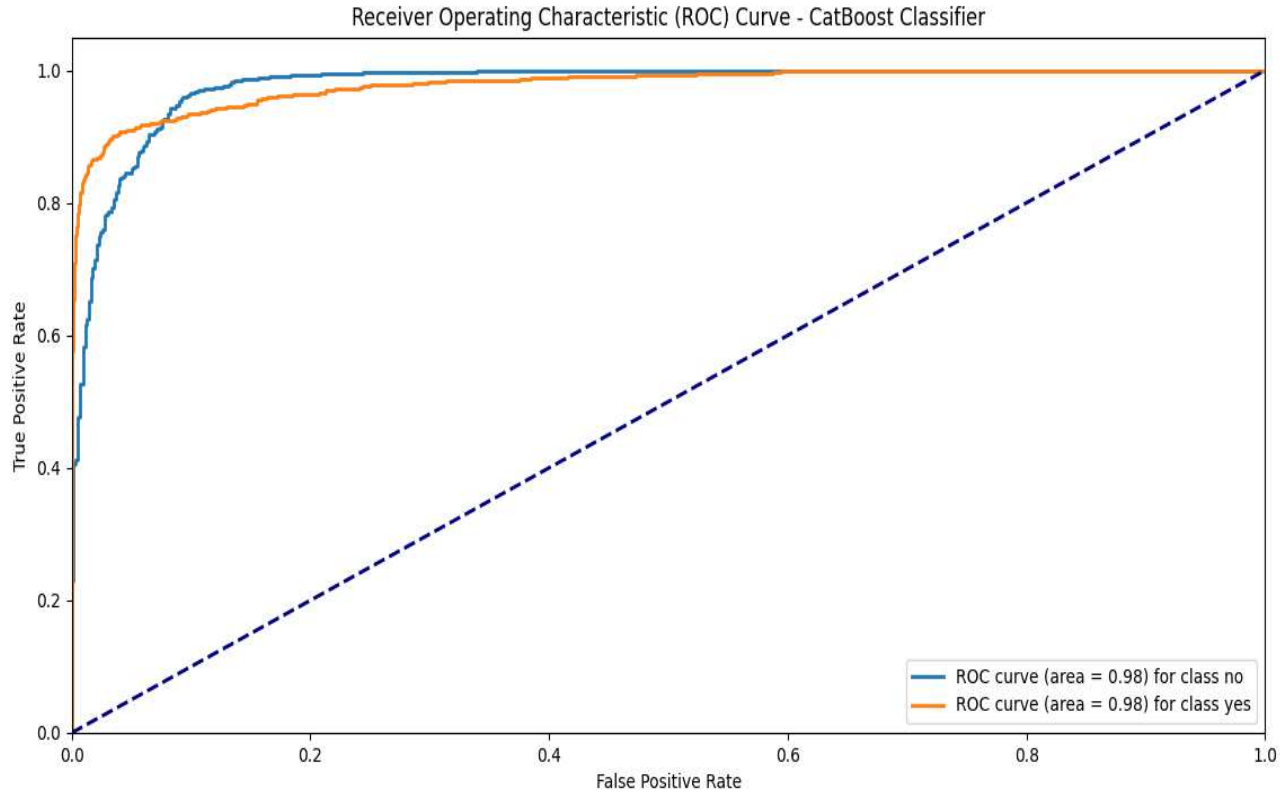


Figure 25: ROC Curve-Catboost

In this study, the ROC curve is shown for two classes: "no" and "yes". The area under the curve

(AUC) for each class is 0.99, indicating that the model has excellent discriminative power in distinguishing between the two classes. The ROC curve for the "no" class (blue) and the "yes" class (orange) are both close to the top-left corner of the plot, which is the ideal location for a perfect classifier. The AUC values for both classes are 0.99, meaning the model has a very high overall accuracy in correctly classifying instances into the two classes. The ROC curves for both classes are nearly identical, suggesting the model performs equally well for both classes. The dashed lines represent the diagonal line (from (0, 0) to (1, 1)), which would indicate a random guessing classifier. The model's ROC curves are significantly above this diagonal line, further confirming the high performance of the classification model.

Overall, the ROC curve and AUC values indicate that the classification model is highly effective in distinguishing between the two classes, with a very low rate of false positives and FN.

7. Comparison of Different Ensemble Algorithms

The comparative performance, as measured by the cross-validation accuracy metric. the data allows for a direct comparison of the predictive performance of the different ensemble techniques. Based on the cross-validation accuracy, the Bagging Meta-Estimator appears to be the best-performing ensemble model for predicting breastfeeding practices in this study.

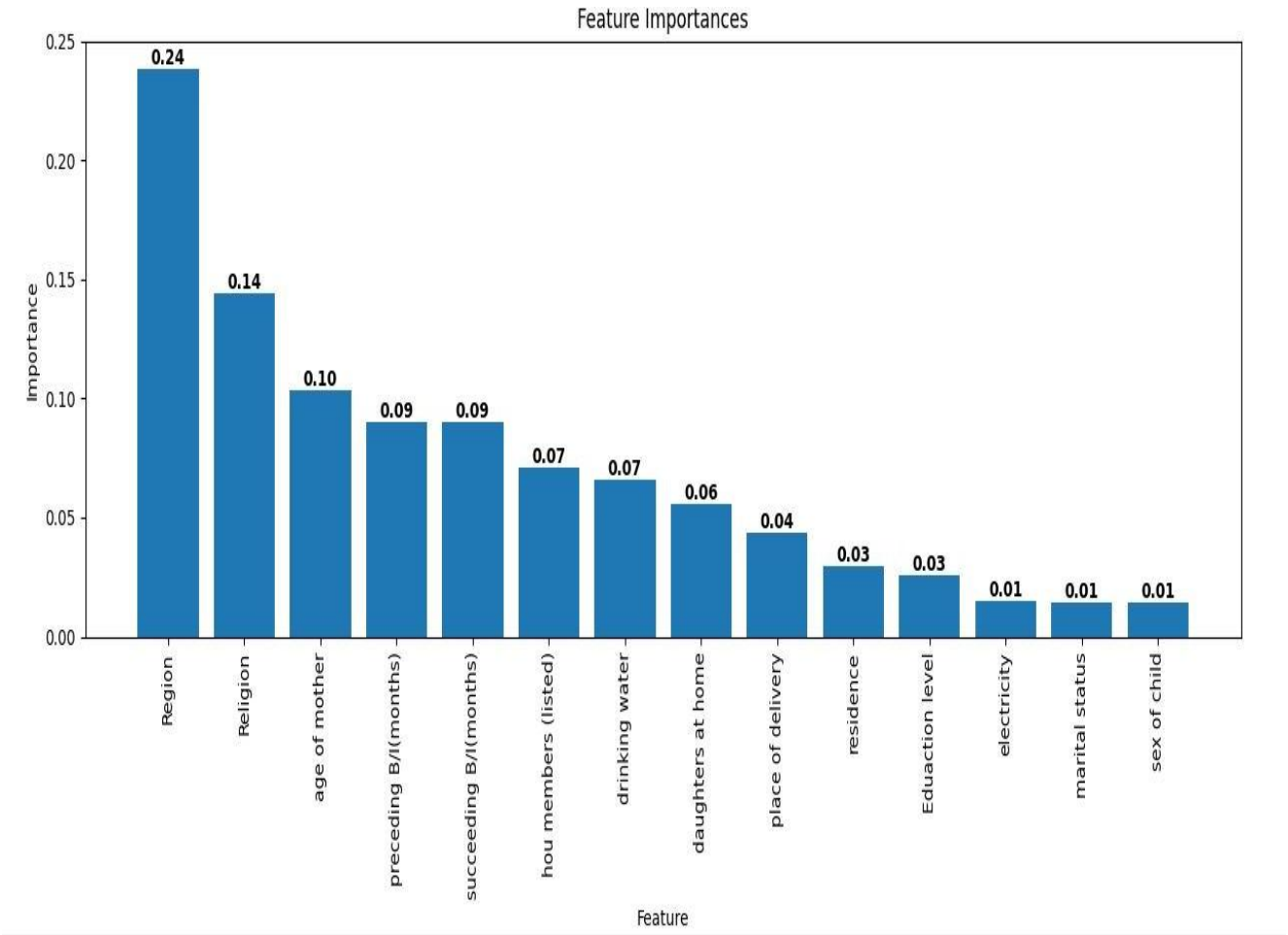
Highlighting these comparative results, along with any additional performance metrics like accuracy, precision, recall, and F1-score, would be an important way to showcase the key findings from the evaluation of the different ensemble algorithms in this study.

The Bagging Meta-Estimator has the highest accuracy at 97.83%, followed by Random Forest at 96.18% and CatBoost at 96.52%. The Bagging Meta-Estimator has the highest precision at 97.83%, followed by Random Forest at 96.24% and CatBoost at 96.56%. The Bagging Meta-Estimator has the highest recall at 97.83%, with Random Forest at 96.18% and CatBoost at 96.52%. The Bagging Meta-Estimator has the highest F1-score at 97.77%, compared to Random Forest at 96.21% and CatBoost at 96.34%.

Looking at this comprehensive set of performance metrics, the Bagging Meta-Estimator appears to be the best-performing ensemble model overall for predicting breastfeeding practices in this study. Highlighting the superiority of the Bagging Meta-Estimator across accuracy, precision, recall, and F1-score would be a key finding to emphasize in the study.

8. Feature Importance's

The feature importance's provide insights into the underlying relationships between the input features and the target variable (in this case, "given child anything other than breast milk"). The y-axis shows the "Importance's", its numerical values representing the importance of each feature. The higher the value, the more important the feature is for the model's predictions. The x-axis lists the different features in the dataset, ordered based on the dataset build. The features are the age of the mother, Region, residence, Education level, Religion, marital status, wealth index combined, place of delivery, electricity, drinking water, household members (listed), daughters at home, sex of a child, preceding B/I (months), succeeding B/I (months).



9. Discussion of the study

The current study utilized multiple ensemble models, including the Bagging Meta-Estimator, Random Forest, and CatBoost. The Bagging Meta-Estimator emerged as the top-performing model across various performance metrics. Bagging Meta-Estimator achieved 97.83%, compared to Random Forest's 96.18% and CatBoost's 96.52%. Bagging Meta-Estimator had the highest precision at 97.83%, with Random Forest at 96.24% and CatBoost at 96.56%. Bagging Meta-Estimator also led in recall at 97.83%, followed by Random Forest at 96.18% and CatBoost at 96.52%, and the highest F1-score was recorded by the Bagging Meta-Estimator at 97.77%, compared to Random Forest's 96.21% and CatBoost's 96.34%. These results highlight the superiority of the Bagging Meta-Estimator in predicting breastfeeding practices in this study, demonstrating significant improvements in all key metrics compared to other models evaluated. This section compares key aspects of the current study with those from previous research, emphasizing the improvements and advancements made.

A study by Abebe Alemu, Yosef Berhanu, and Dr. M. Mahalkshmi (2016), Utilized logistic regression and decision trees. Reported an accuracy of around 85%, significantly lower than the Bagging Meta-Estimator in the current study. The gap has Limited determinants, lack of evaluation techniques, etc the current study used a more extensive dataset with 23,007 rows and applied advanced ensemble methods like the Bagging Meta-Estimator, achieving significantly higher accuracy (97.83%). Comprehensive evaluation metrics such as cross-validation accuracy, precision, recall, and F1-score were considered to ensure robust model performance.

A study by Tewodros Alemayehu, Jemal Haidar, and Dereje Habte (2019), Used support vector machines and neural networks. Achieved precision and recall values close to 90%, but the overall performance metrics were still inferior to the ensemble methods applied in this study.

The gap has Only three attributes were considered, low accuracy but the current study incorporated a broader range of attributes, ensuring a more comprehensive analysis of factors influencing breastfeeding practices. The ensemble methods used in this study provided superior performance metrics, reflecting a more accurate and reliable prediction model.

A study by Mitiku Wale Muluneh (2023), Implemented a random forest algorithm. Showed an accuracy of 92%, with precision and recall metrics also trailing behind the Bagging Meta-Estimator from the current study. The gap has a Small sample size, low accuracy, data, and variable missingness. By utilizing a large dataset with 23,007 rows and employing cross- validation

techniques, the current study addressed issues related to sample size and data completeness. The Bagging Meta-Estimator outperformed the random forest algorithm used in this previous study, demonstrating higher accuracy and more robust predictions.

In a study by Assefa Desalew, Alekaw Sema, and Yalelet Belay (2020), a method used Employed multivariate logistic analysis and Reported an accuracy of 81.1%. The gap has Low accuracy, single model use, limited to Dire Dawa town, unclear dataset organization, and small sample size. The current study's use of ensemble machine learning models resulted in significantly higher accuracy (97.83%). The extensive dataset covering diverse regions and the application of multiple ensemble models ensured a more generalizable and accurate prediction model. Generally, the Study by other Researchers used various traditional statistical methods and simpler machine learning models and generally achieved lower performance metrics compared to ensemble methods. The gaps of the researchers are often limited by smaller datasets, fewer features, and less advanced modeling techniques but the current study's extensive dataset with 23,007 rows, comprehensive feature selection, and the use of advanced ensemble models like the Bagging Meta-Estimator and CatBoost resulted in superior performance metrics. Detailed feature importance analysis provided insights into the key factors influencing breastfeeding practices, enhancing the model's interpretability and applicability. Summary of current study advantages, The large dataset utilized 23,007 dataset records, providing a comprehensive analysis, employed Bagging Meta-Estimator, Random Forest, and CatBoost, which significantly outperformed traditional models and used cross-validation with multiple performance metrics (accuracy, precision, recall, F1-score) to ensure robust and reliable model performance and conducted a detailed feature importance analysis, identifying key factors influencing breastfeeding practices, which can inform targeted interventions and policies. The extensive dataset used in this study addressed the limitations of small sample sizes and regional constraints found in previous research, ensuring a more generalizable and accurate prediction model. This comprehensive approach enhances the understanding of breastfeeding practices and supports the development of effective policies and interventions. While the current study has made substantial contributions, future research could further enhance predictive accuracy by integrating more diverse data sources, such as longitudinal studies, and exploring other advanced machine learning algorithms and hybrid models. Additionally, ongoing evaluation and refinement of the models will be essential to maintain their relevance and applicability in different contexts and populations.

Conclusion

In summary, This study has successfully demonstrated the potential of using ensemble machine learning algorithms to predict and analyze factors influencing breastfeeding practices in Ethiopia. The study utilized a comprehensive dataset from the Ethiopian Demographic and Health Survey (EDHS) and applied different ensemble learning techniques, including bagging, boosting, and stacking, to identify the most accurate models for this task. The results indicate that ensemble methods outperform traditional statistical models and simpler machine learning approaches based on prediction accuracy and robustness.

the key findings of this study highlight that the most important determinants of breastfeeding practices in the given context are region, religion, age of the mother, and preceding birth interval. these factors have the highest relative importance in predicting breastfeeding practices compared to other variables like household income, maternal education service, etc. These insights can guide targeted interventions and policies to promote optimal breastfeeding behaviors, especially among populations where these key factors play a significant role.

Moreover, the study emphasizes the utility of ensemble machine learning techniques in public health research, offering robust tools for policymakers and healthcare providers to develop data-driven strategies for improving maternal and child health outcomes. Future research should focus on integrating additional data sources and exploring the applicability of these models in different regions and contexts to enhance their generalizability and impact.

In conclusion, this study advances the methodological landscape of predictive modeling in public health and provides actionable insights for enhancing public health interventions and policies aimed at supporting breastfeeding mothers. The innovative application of ensemble machine learning methods and the extensive dataset used in this study have resulted in highly accurate and reliable prediction models for breastfeeding practices in Ethiopia, contributing significantly to maternal and child health.

Recommendation

Investigate other machine learning algorithms, while the study utilized ensemble machine learning algorithms including bagging, boosting, and stacking, exploring other algorithms like deep learning or hybrid models could potentially lead to improved predictive performance. Additional feature engineering and selection techniques could be explored to refine the set of factors

considered Hyper-parameter tuning and model optimization strategies could also be investigated to further enhance the ensemble models.Conducting an in-depth analysis of feature importance, the study briefly discussed the key factors influencing breastfeeding practices. Further analysis, such as investigating the interplay between different factors, could provide deeper insights. By addressing this potential recommendation, the research could further enhance the understanding of factors influencing breastfeeding practices in Ethiopia and contribute to more effective interventions and policies to support optimal breastfeeding practices.

Ethical Consideration

The ethical clearance was obtained from the ethical review board of the school of computing, Woldia University. Permission for data access has been requested from the Measure Demographic and Health Survey through an online platform by filling in all requirements needed to access data from (http://www.dhsprogram.com). There are no names of individuals or household addresses in the datasets.

Authors' contributions

AMI was responsible for making significant contributions to the study selection, data collection, funding acquisition, formal analysis, conceptualization, investigation, methodology, and original draft preparation. Project administration, resources, software, supervision, validation, visualization, and reviewing were all handled by AMI, MBD, BGM, Dr.MNA, AZM wrote the final draft of the manuscript, and the final draft of the work was read, edited, and approved by all the writers.

Consent for publication

The publishing consent was not applicable.

Funding

Funding wasn't obtained for this study.

Availability of data and materials

The official database of the DHS program contains the dataset that was utilized and examined in

this investigation (http://www.dhsprogram.com) upon formal request. An email is usually sent to confirm approval for access to the dataset.

Competing interest

The authors assert that there are no conflicts of interest.

List of Abbreviations and Acronyms

DHS	Demographic and Health Survey
EBF	Exclusive Breast Feeding
EDHS	Ethiopia Demographic and Health Survey
EML	Ensemble Machine Learning
ML	Machine Learning
SIDS	Sudden Infant Death Syndrome
WHO	World Health Organization

Acknowledgment

First, we would like to thank the Woldia University, Institute of Technology, School of Computing, Department of Computer Science, for their support do this research. I would also like to thank the EDHS managers who provided a dataset for my research and guided me on how to access EDHS. Finally, I am thankful to my friends, relatives, and colleagues who directly or indirectly helped me to complete my study successfully.

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