Research Square

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Stacking Ensemble Models for Predicting Digital Payment Adoption: A Comprehensive Machine Learning Analysis of Global Findex 2025 Data

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Research Article

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Abstract

This study analyzes factors affecting digital payment system adoption using machine learning methods with the 2025 Global Findex dataset. The analysis encompasses 144,090 adults from 141 countries. Key dependent variables were filtered through feature selection processes. In the feature engineering phase, new variables were derived, including education-internet usage interaction, income source diversity, and financial inclination. Subsequently, hyperparameter optimization was performed using Optuna for advanced boosting methods including XGBoost, LightGBM, and CatBoost. Voting and stacking ensemble techniques were evaluated to identify optimal model combinations. The experimental results demonstrated that the combination of LightGBM-XGBoost models with ExtraTrees meta-learner stacking achieved 93.04% accuracy. Model outputs were evaluated using SHAP library for feature relationship analysis. Results indicate that education level, internet access, and income level demonstrate strong positive relationships with digital payment adoption. Model findings underscore the critical importance of education and digital infrastructure in enhancing access to digital financial services.

1. Introduction

Digital payments have become an integral component of the global economy and have transformed access to financial services worldwide. The rapid adoption of digital payment systems, particularly in the post-COVID-19 period, has played a critical role in advancing financial inclusion [1]. Financial inclusion is defined as a process that enables individuals and businesses to access financial products and services (transactions, payments, savings, credit, and insurance) that are appropriate, affordable, and accessible to their needs [2]. This development is of vital importance for economic growth and poverty reduction, promoting more equitable economic development by facilitating the participation of marginalized communities in the formal economy [2]. The World Bank's Global Findex database is recognized as a unique resource for monitoring global financial inclusion [3]. The 2025 update provides new insights into the interactions between mobile technology, internet usage, and financial inclusion, presenting comprehensive data that reflects the rapid adoption of digital payment systems

Literature reviews examining factors influencing digital payment adoption behavior demonstrate that demographic characteristics such as education level, income, age, and geographic location have significant impacts on financial inclusion and the utilization of digital financial services [4]. Specifically, it has been noted that internet access enhances the opportunity for inclusive development by reducing communication costs and increasing information flow among market participants. Higher education levels have been associated with faster adoption of digital financial services. Indeed, individuals without education are less likely to utilize digital financial services [5]. Furthermore, it is emphasized that digital literacy skills and internet usage play important roles alongside education in the adoption of digital financial services [6], [7]. Urban residents tend to adopt digital financial services more rapidly than individuals in rural areas [8]. However, despite the potential of digital payments, barriers such as insufficient digital literacy and awareness, inadequate security measures, data privacy concerns, low internet speeds, and lack of reliable internet access impede their adequate adoption, particularly in

developing countries [9]. This situation demonstrates that a significant portion of the population remains excluded from digital payment services [10].

While traditional econometric methods have frequently been employed to model financial behavior, machine learning approaches can provide higher accuracy than conventional models in banking and payment literature [11], [12]. Traditional methods may be limited in capturing complex, non-linear interactions between variables and high-dimensional data structures [13]. In recent years, gradient boosting algorithms have demonstrated high success in financial forecasting problems [14], [15]. However, although such deep neural networks and gradient boosting tree models are quite powerful in capturing feature interactions and non-linear relationships, they may be prone to risks of overfitting, data leakage, and lack of generalization. To mitigate these risks and obtain more stable and accurate predictions, ensemble learning approaches have emerged as prominent solutions [16].

In this study, to overcome the limitations of traditional approaches and build more robust predictive models while reducing the risk of overfitting, we employed various ensemble methods alongside powerful base models such as CatBoost [17], XGBoost [18], and LightGBM [19] including stacking ensemble that combines the strengths of different algorithms [16], [20]. The combined use of machine learning models and the Global Findex dataset in financial inclusion studies is documented in the literature. These studies have determined hyperparameter settings using Bayesian optimization and compared their performance [14]. However, in the existing literature, we have not found a study that employs such a comprehensive ensemble approach on Global Findex 2025 microdata (supported by detailed analyses such as stacking methods with hyperparameter optimization of various gradient boosting algorithms, SHAP value analysis, and learning curves) to model digital payment behaviors. This study carries significant originality both methodologically in employing advanced machine learning techniques and in analyzing the most current Global Findex 2025 dataset. In this context, the primary objective of this study is to deeply analyze the socio-economic and digital access factors influencing digital payment adoption behavior and to develop a highly accurate, interpretable predictive model.

2. Materials and Methods

This study employed various ensemble methods alongside powerful base models such as CatBoost, XGBoost, and LightGBM including stacking ensemble that combines the strengths of different algorithms [21], [22]. In order to overcome the limitations of traditional approaches and build more robust predictive models while reducing the risk of overfitting. A quantitative approach using machine learning techniques was adopted to predict digital payment adoption behaviors. The methodology encompasses stages of data collection, preprocessing, feature selection and engineering, model development, and evaluation.

2.1 Data and Feature Engineering

This study utilizes the current Global Findex microdata collected by the World Bank in 2024 and published in 2025 [3]. As illustrated in Fig. 1, digital payment adoption rates vary considerably across the 141 economies included in this study, reflecting significant disparities in financial inclusion progress globally.

This dataset contains comprehensive financial inclusion data representing 144,090 individuals aged 15 and above, selected from 141 economies. The dependent variable in this study is the 'anydigpayment' variable, coded in binary format, representing individuals' use of any digital payment method. After removing 41,136 observations containing missing values in the dependent variable, analyses were conducted on 102,954 valid cases. This cleaned dataset provides a robust foundation for analyzing digital payment behaviors.

The raw dataset initially contained 183 variables. To enhance the efficiency of this variable set in analytical processes, a two-stage feature management strategy was implemented. First, using CatBoost based feature importance analysis, 66 variables were selected from the initial 183 based on their relative importance in predicting digital payment adoption. Subsequently, variables exhibiting excessive correlation or logical dependencies that could lead to data leakage were eliminated, resulting in 42 independent variables for the final model. Based on insights obtained from literature review and exploratory data analysis, four synthetic variables were derived to enhance the model's predictive power:

- **educ_internet**: A multiplicative variable indicating the interaction between education level and internet usage status.
- **sources_income**: Represents the sum of different income sources such as salary, pension, and agricultural income.
- **financially_inclined**: A composite variable integrating financial tendencies such as saving behavior, borrowing history, and credit card ownership.
- **age_situation**: A variable categorizing individuals' age groups.

With the derivation of these synthetic variables, the number of variables in the final dataset reached 46. These features were designed to more comprehensively model digital payment adoption behavior.

2.2 Methodological Approach and Model Selection

Digital payment adoption behavior was initially modeled using both classification and regression approaches. As a result of the analyses, classification models yielded superior results in terms of performance metrics; therefore, the remainder of the study treated this problem as a binary classification problem. Gradient boosting algorithms (XGBoost, LightGBM, and CatBoost) which have demonstrated high success in financial inclusion research, were employed as base models. Gradient boosting algorithms create a strong predictive model by sequentially combining weak learners (typically decision trees). Each new tree is trained to correct the errors of the previous tree. XGBoost provides a scalable and distributed gradient boosting framework. The objective function in Eq. (1) includes a regularization term that controls model complexity while improving prediction accuracy.

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i,\ \widehat{y}_i^{(t-1)} + f_t\left(x_i\right)\right) + \Omega\ \left(f_t\right)$$

1

Where:

- l : The loss function measuring the difference between predicted and actual values. For binary classification tasks, log-loss is employed.
- $\widehat{y}_i^{(t-1)}$: The cumulative prediction from all previous iterations (t-1) for the i-th observation.
- $f_t\left(x_i\right)$: The prediction from the newly added tree f_t for the i-th observation.
- f_t : The new tree added to the model in the t-th iteration.
- Ω : The regularization term penalizing model complexity to prevent overfitting
- y_i : The actual value for the i-th observation.
- n : The total number of observations.
- t : The current iteration number.

LightGBM employs the same additive training strategy as XGBoost but with a different tree growth strategy, leaf-wise instead of level-wise, in contrast to traditional level-wise growth strategies. This strategy optimizes the objective function more efficiently by splitting the leaf with the highest gradient sum at each iteration. This approach provides faster training times and high performance, particularly on large datasets. The gain calculation in LightGBM is expressed as shown in Eq. (2):

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{\left(G_R\right)^2}{H_L + H_R + \lambda}\right] - \gamma$$

2

Where:

- G_L , G_R: Sum of first-order gradients in left and right leaves, respectively.
- H_L , H_R: Sum of second-order gradients in left and right leaves, respectively.
- λ : L2 regularization coefficient controlling the magnitude of leaf weights.
- γ : Leaf complexity penalty coefficient.

CatBoost employs the same additive boosting framework as XGBoost and LightGBM. One of the fundamental features distinguishing CatBoost from prior GBDT techniques is its use of oblivious (symmetric) tree structures, which apply the same split rule to all nodes at each depth level. This depth-filling structure produces exactly 2^d leaves at each iteration, where d is the tree depth. This design offers two key advantage; computational efficiency, and stable generalization performance.

Consequently, CatBoost demonstrates particularly stable performance on datasets with numerous categorical variables or complex feature interactions.

Another distinguishing aspect of CatBoost is its ability to process categorical features directly without requiring one-hot or label encoding preprocessing. This is accomplished through computing target-based statistics for category values in a regularized form. The target encoding for a categorical feature is computed as presented in Eq. (3):

$$\widehat{x}_{k,i} = \frac{\sum_{j=1}^{n} \mathbf{1}(x_{j,i} = x_{k,i})\backslash\mathrm{hspace}\{0.17\mathrm{em}\}Y_j + \alpha\, P}{\sum_{j=1}^{n} \mathbf{1}(x_{j,i} = x_{k,i}) + \alpha}$$

3

Where:

- $x_{k,i}$: The categorical feature value of the k-th example (i-th sample).
- $\widehat{x}_{k,i}$: The transformed numeric value based on target statistics.
- Y_j : The target variable value for observation j.
- α : The smoothing parameter controlling regularization strength.
- P : the prior probability, the global mean of the target variable across the entire dataset.
- $\mathbf{1}(\cdot)$: The indicator function.

2.3 Hyperparameter Optimization and Ensemble Learning

Hyperparameter optimization was performed using the Optuna library for XGBoost, LightGBM, and CatBoost models to maximize their performance. Optuna is a framework with a define-by-run API that dynamically adjusts model parameters using Bayesian optimization and other advanced algorithms [23]. This approach yielded noticeable improvements in model accuracy and ensured configuration with optimal parameter sets [24]. The optimization process enhanced the models' generalization ability, contributing to obtaining more consistent and reliable results.

To reduce the risk of overfitting and build more robust predictive models, ensemble learning approaches were employed. This study evaluated both Voting and Stacking ensemble techniques [22]. Voting ensemble is a technique that combines predictions from multiple base models to reach a final decision. This study evaluated both hard voting and soft voting approaches. Stacking is a two-layer ensemble method that combines the strengths of different algorithms. Base models' class probability predictions serve as features for a meta-learner. ExtraTrees Classifier was employed as the meta-learner in this study [25]. The class probability predictions from the base models were presented to the meta-learner as a new feature matrix.

2.4 Model Evaluation and Validation

The 5-fold cross-validation method was applied to evaluate model performance and optimize hyperparameters. The dataset was divided into 5 subsets; in each iteration, one subset was used as test data while the other four were used for training. This process was repeated 5 times, and the average of performance metrics across iterations served as the model's final performance measure. This method measured the model's generalization ability across different data subsets.

Model performance was evaluated using the accuracy [26], f1-score [27], and ROC-AUC [28] metrics.

2.5 Model Interpretability

To render the model's decision-making process transparent and interpret the findings, the SHAP (SHapley Additive exPlanations) library was employed. SHAP is based on cooperative game theory and Shapley values, providing a unified framework for understanding feature contributions to model predictions [29]. SHAP analysis at the meta-learner level quantitatively determined the contributions of the base models to the final decision.

3. Results

3.1 Classification vs. Regression Approach

In the initial phase of the study, two different approaches—classification and regression-to-binary conversion—were tested for XGBoost classification and regression models to predict digital payment usage. The performance comparison presented in Fig. 2 demonstrates that the classification approach provided superiority across all metrics.

In light of these results, considering the binary nature of digital payment usage, the direct classification approach was determined to be more suitable for the problem and was adopted for the remainder of the study.

3.2 Hyperparameter Optimization Results

Hyperparameter optimization of XGBoost, CatBoost, and LightGBM models using the Optuna library improved the models' accuracy metrics. When addressing digital payment adoption behavior as a classification problem, models were configured with optimal parameters, enhancing the reliability of comparative analyses. This optimization process improved overall model performance, contributing to obtaining more consistent and generalizable results. As shown in Fig. 3, the fold-based model accuracies before and after Optuna optimization clearly demonstrate the impact of hyperparameter optimization on model performance.

The graph reveals a notable increase in accuracy following hyperparameter optimization compared to unoptimized base models. While this improvement enhanced the models' overall predictive power, it demonstrates that optimization provides a limited but statistically significant contribution

3.3 Ensemble Methods Comparison

Different base model structures were tested in binary and triple combinations in the ensemble approach, with general accuracy distributions presented in Fig. 4. Single gradient boosting models are presented under the "Single" heading, while ensemble models are examined under their respective headings.

Soft voting yielded more stable results compared to hard voting, as illustrated in Fig. 5, because it combines information at the probability level by considering probability distributions from each base model, creating a more nuanced and precise decision mechanism.

The soft voting approach, particularly in combining heterogeneous models, provides more consistent and reliable results through greater information utilization in the decision-making process. This supports the preference for soft voting in model selection and ensemble learning strategies. Figure 6 shows the classification performance of four different combinations of meta-learners and base models for the stacking boosting models.

The results demonstrate that all configurations achieved high accuracy values in the range of 0.9287–0.9305. A notable finding is that the same meta-learner demonstrates a performance variation of 0.0018 with different base model combinations, emphasizing the critical importance of the composition of first-level predictors.

3.4 Best Performing Model Configuration

The highest performance was achieved with the XGBoost-LGBM base combination and ExtraTrees meta-learner in the stacking architecture, reaching 0.930464 accuracy as shown in Fig. 7. The fact that all four top-ranking models employ a stack structure and prefer combinations containing XGBoost and LGBM indicates that these algorithms' complementary learning characteristics create a synergistic effect.

The notable positioning of the LGBM model optimized with Optuna as a single model (LGB_AFTER) in sixth place with 0.930250 accuracy demonstrates that even a well-calibrated single model can produce competitive results. The marginal superiority of soft voting over hard voting supports the advantages of probability-based decision fusion.

3.5 Final Model Architecture

The two-layer stacking classification architecture that achieved the best performance in evaluation metrics was adopted as the final model. The base layer (Level-0) consists of XGBoost and LightGBM models trained with optimized hyperparameters. Within the stacking mechanism, base models were trained using 5-fold cross-validation and class probability predictions were generated for validation data at each fold. The probabilities obtained through the predict_proba method were combined to create a new feature matrix serving as input to the meta-learner.

Meta-learner level SHAP analysis clearly demonstrates in Fig. 8 how the stacking meta-learner interprets the positive class probability predictions of base models and transforms them into final classification decisions.

The meta-learner integrates predictions from XGBoost and LightGBM with different weights (contributing 58% and 42% respectively), determining the direction and magnitude of each base model's contribution.

At the meta-learner level (Level-1), ExtraTrees Classifier was employed due to its high model diversity and low overfitting risk, achieving the highest performance among all stacking architectures in evaluation metrics. The meta-model integrated probability-based outputs from base models to generate final class predictions. This structure provides more stable and generalizable classification performance compared to individual models.

3.6 Learning Curve and Overfitting Analysis

The learning curve analysis presented in Fig. 9 demonstrates the stacking model's generalization performance as the training dataset grows. At small data sizes, the high training F1-score and lower validation F1-score indicate the model's initial tendency toward overfitting. As training data increases, the gap between training and validation F1-scores narrows, and validation performance rises consistently, indicating that the model's generalization ability strengthens with more data. The validation performance reaching a plateau at large data sizes reveals that additional data increases provide limited gains and that the model has achieved balanced learning

4. Discussion

This study presents important findings regarding the factors influencing digital payment adoption behavior and the effectiveness of ensemble methods in modeling this behavior. Particularly, the multiplicative interaction between education level and internet access, parallel to similar studies in the literature, emphasizes that both factors must be addressed in an integrated manner rather than considering infrastructure or education alone in the adoption of digital financial services. In our study, this interaction exhibits 18% stronger correlation compared to linear sums, supporting findings in this area of research [30], [31]. This demonstrates that investments in internet infrastructure, unless combined with simultaneous digital literacy training programs, may be insufficient to produce expected fintech adoption increases.

The results obtained regarding model performance clearly demonstrate the superiority of the stacking ensemble approach compared to individual models. This superiority can be explained by the bias-variance trade-off principle in machine learning [32]. While algorithms such as XGBoost typically exhibit low bias but high variance, LightGBM demonstrates moderate bias and variance. Meta-learners such as Extra Trees possess the potential to reduce total variance by smoothing the errors of base models [33]. In the stacking architecture, the meta-learner learns the strengths of base models in different data subregions, increasing overall generalization capacity. This confirms that the complementary learning characteristics of different algorithms create a synergistic effect and validates the power of ensemble methods in modeling such complex financial behaviors [34].

Model interpretability analysis using SHAP values quantitatively determined the contributions of base models such as XGBoost and LightGBM to the final decision. This analysis revealed that XGBoost's

positive class probability predictions carry 58% weight and LightGBM predictions carry 42% weight in the model's decision, providing transparent insight into how the meta-learner weights base model outputs. This renders interpretable the decision mechanisms of machine learning models that are typically considered "black boxes."

The model's tendency toward misclassification among low-income and rural populations indicates structural barriers to digital financial inclusion [35]–[37]. This is related to factors such as digital literacy and infrastructure deficiencies, security concerns, and low internet speeds. Detailed examination of this segment's misclassification and development of targeted solutions for these groups will play a critical role in achieving financial inclusion objectives.

5. Conclusion

This study presents important findings by employing stacking ensemble approaches to predict digital payment adoption behaviors on the Global Findex 2025 dataset. Correlation analyses supported that education level, internet access, and income level exhibit strong positive relationships with digital payment usage. The developed stacking approach with LightGBM-XGBoost combination and ExtraTrees meta-model achieved 93.04% accuracy, providing the most current and highest predictive performance in the literature. This success demonstrates that while hyperparameter optimization provides limited contribution, the stacking architecture significantly enhances generalization ability and predictive power.

However, this study has certain limitations. The absence of macroeconomic indicators in the dataset restricts consideration of unobserved heterogeneity at the national level. The ability to capture dynamic behavioral changes in digital payment systems is limited by the cross-sectional nature of the data. Future research should incorporate panel data structures to capture temporal evolution, integrate macroeconomic indicators (inflation rates, GDP growth, regulatory environment), and employ causal inference methods to strengthen understanding of policy intervention effects on digital payment adoption. Additionally, detailed analysis of persistently excluded populations (low-income, rural) with tailored recommendations for targeted interventions would enhance practical policy implications and contribute to achieving financial inclusion objectives.

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Figures

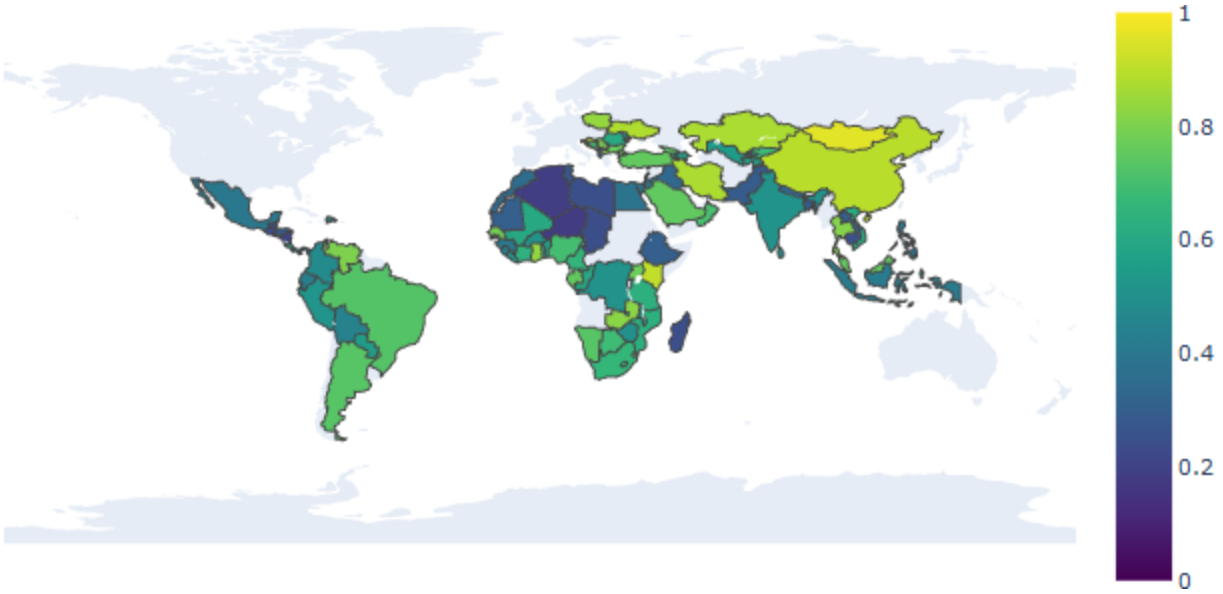


Figure 1

Digital payment adoption rates by country in dataset.

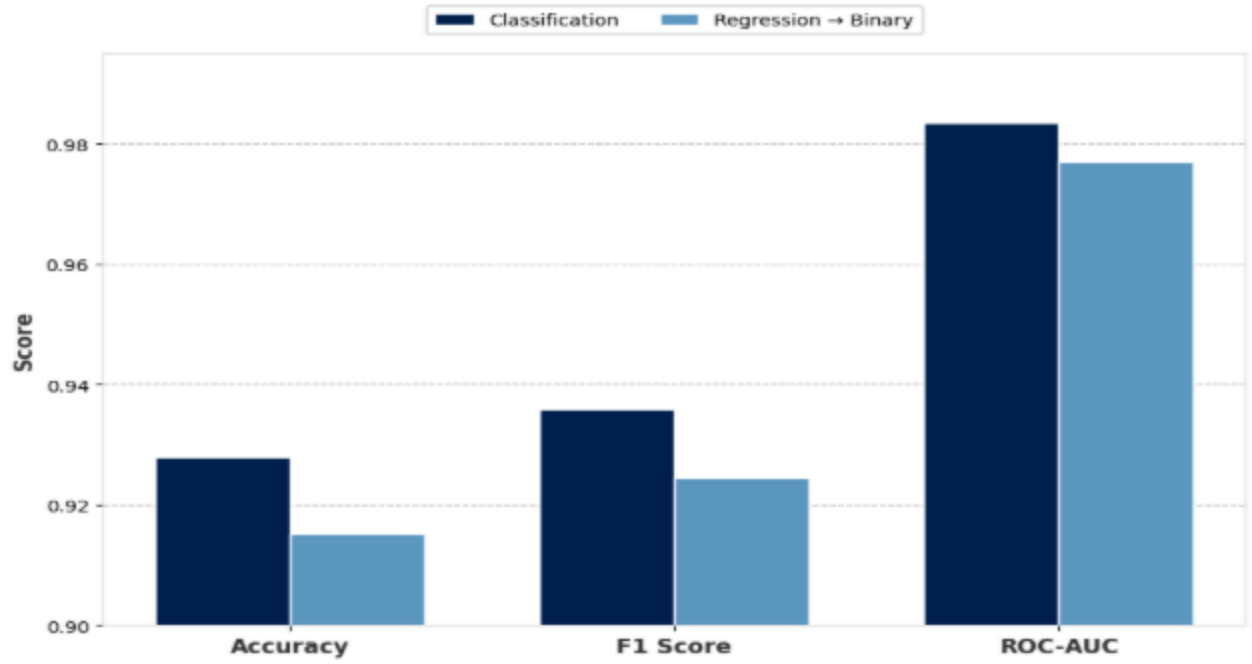


Figure 2

Model performance comparison.

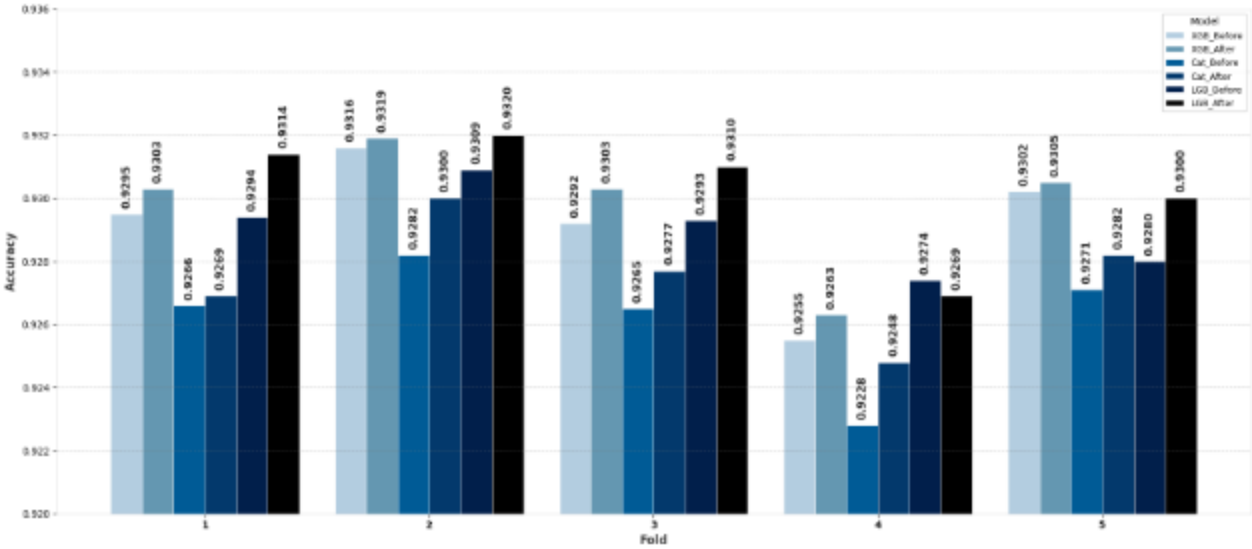


Figure 3

Fold-based model accuracy before and after optuna optimization.

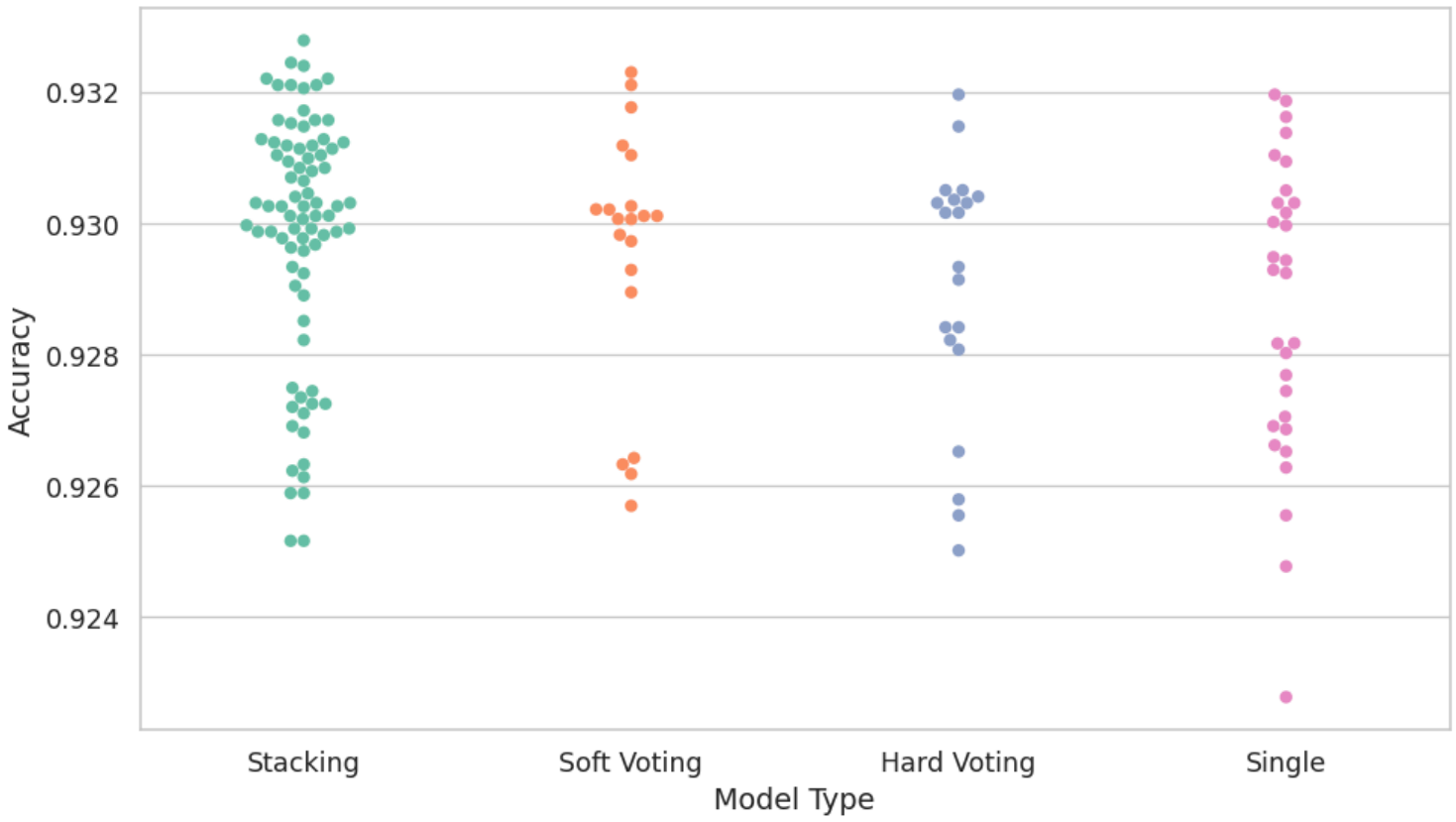
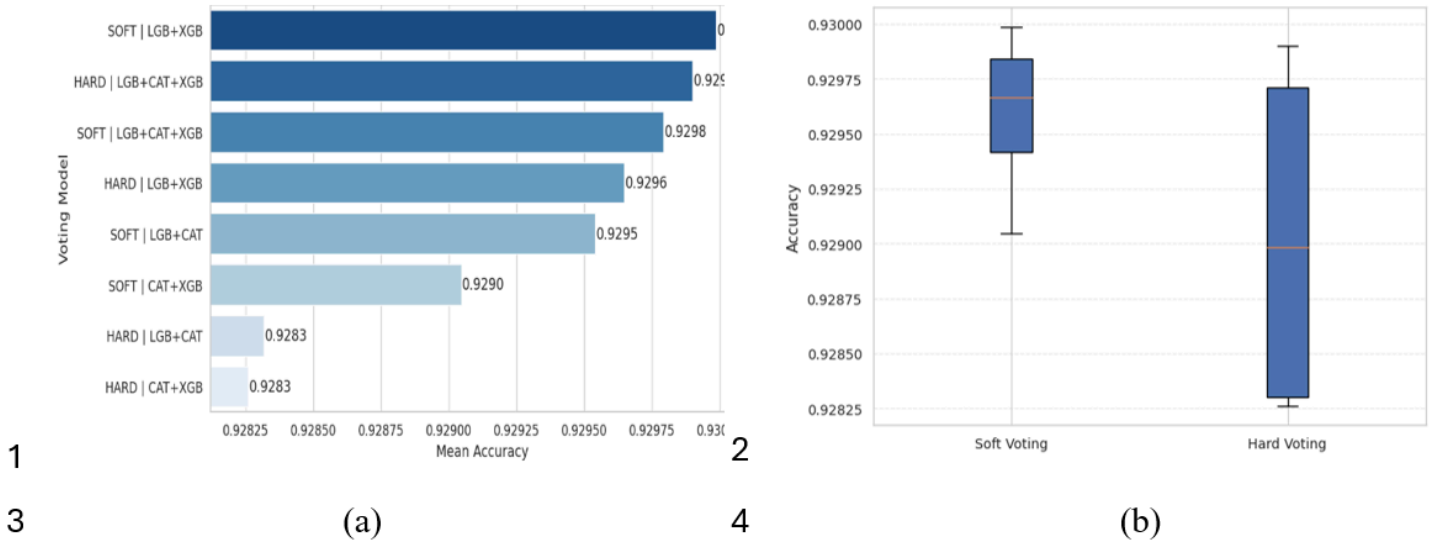


Figure 4

Stacking, voting, and single model accuracy distribution.



1 2

3 (a) 4 (b)

Figure 5

Voting ensemble results: method rankings (a), and soft vs. hard voting accuracy distribution (b).

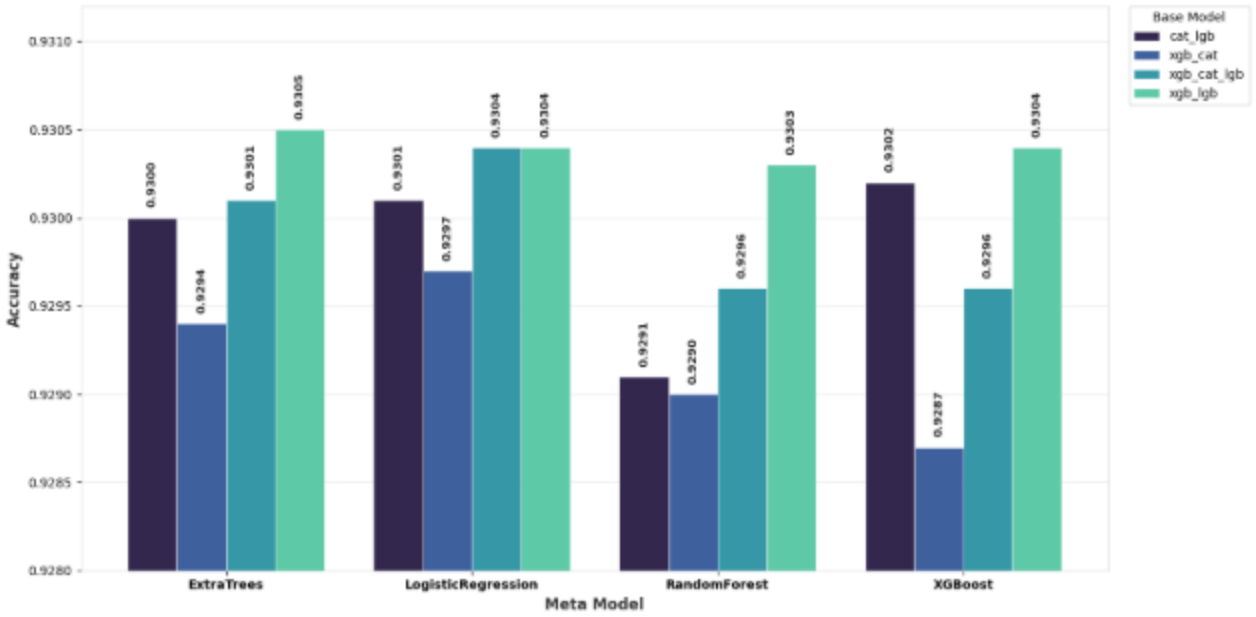


Figure 6

Stacking meta-models accuracy performance.

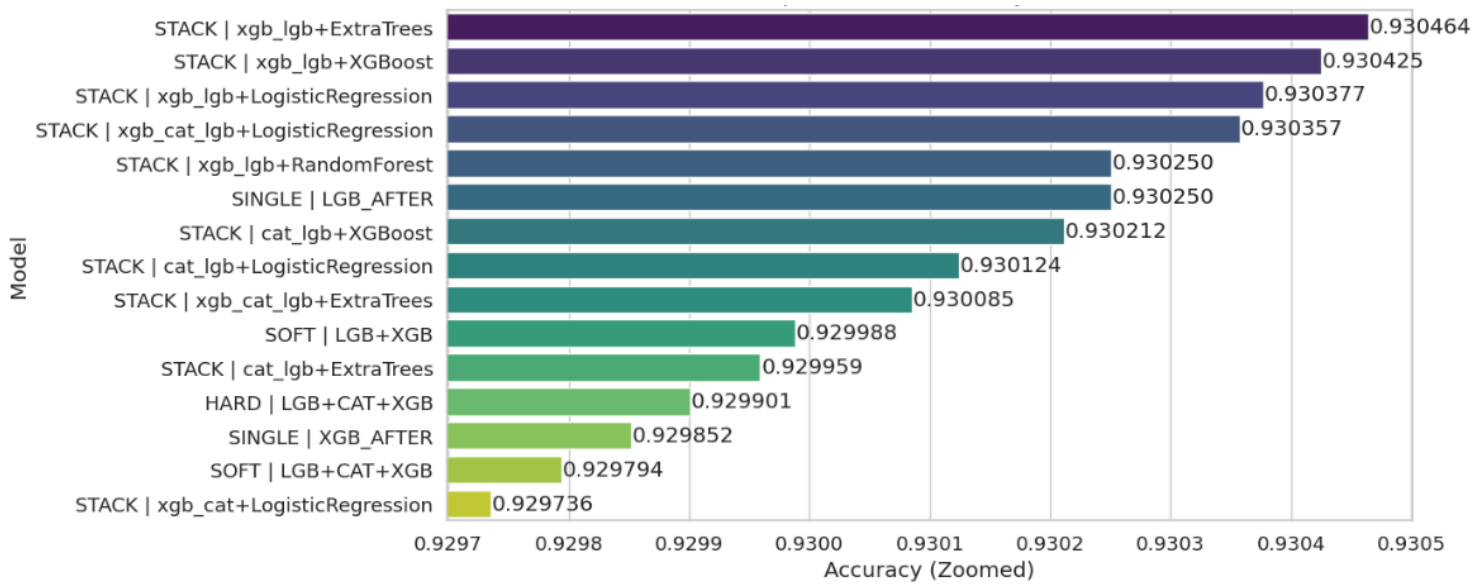
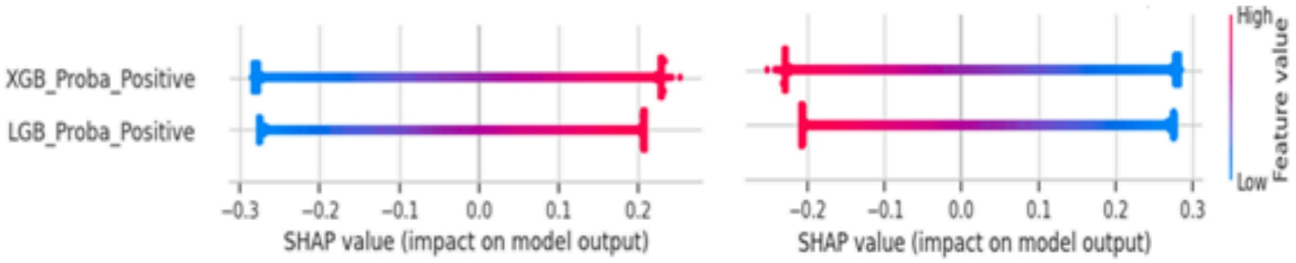


Figure 7

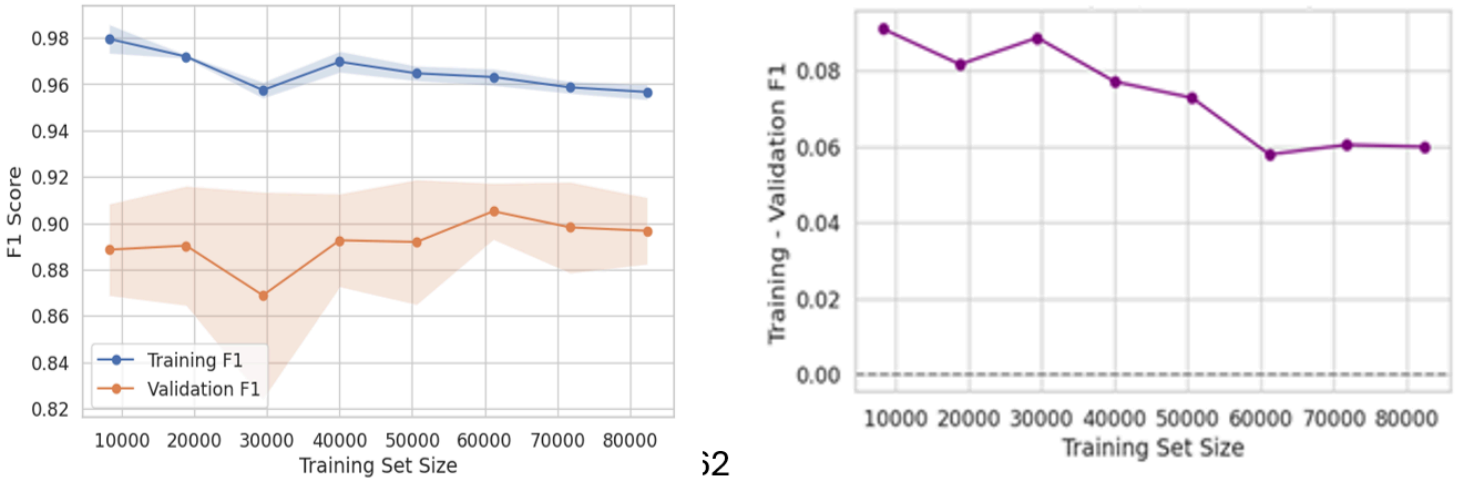
Top 15 Meta and base model combinations.



(a) (b)

Figure 8

Base models' contributions to meta models: (a) positive and (b) negative effects.



(a) (b)

Figure 9

Learning curves and overfitting analysis: (a) training-validation performance and (b) overfitting gap.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- floatimage1.png