Kickstarter Funding Success Prediction Using Interpretable Machine Learning

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Abstract— **Predicting the success of a Kickstarter campaign is a challenging task due to the complexity and various factors involved. Many campaigns that seem promising at the beginning fail to reach their funding targets due to a lack of investor confidence, poor marketing strategies, or unrealistic time and cost estimates. The aim of this study is to assess the performance of several machine learning models Logistic Regression, Decision Tree, Random Forest, XGBoost, LightGBM, Support Vector Machine, and Multi-Layer Perceptron—using metrics such as accuracy, precision, recall, F1 score, and ROC AUC. The top-performing models across all metrics were XGBoost and LightGBM. The Multi-Layer Perceptron was identified as the second-best model in terms of predictive capability. To further enhance performance, a stacking ensemble learning approach was employed, integrating the top three models. This ensemble method was chosen to leverage the unique strengths of each individual model. Although the stacked model's accuracy did not significantly exceed that of the top-performing individual models, it yielded more stable and robust predictions, indicating improved generalization across varying data subsets. Analysis of feature importance revealed that *goal*, *blurb*, *duration*, and *category* are the most influential factors affecting the success of Kickstarter projects. It is recommended that campaign creators prioritize these elements when designing and promoting their campaigns to increase the likelihood of success.**

Keywords— **Machine Learning, Ensemble Learning, Kickstarter, XGBoost, LightGBM, MLP, SVM, Crowdfunding Prediction, Stacking, Model Comparison, Model Evaluation**

I. Introduction

Crowdfunding has become a widely adopted method for innovators, artists, and entrepreneurs to raise funds for business and creative endeavours. Among the various platforms, Kickstarter stands out due to its unique all-or-nothing funding model, where funds are only disbursed if a campaign reaches its funding goal. While this mechanism fosters accountability and trust, it also introduces significant uncertainty, as many campaigns fail to meet their targets for reasons such as unrealistic funding goals, limited exposure, or insufficient backer engagement [1]. These failures can lead to financial loss and wasted time for both creators and backers.

The complex nature of campaign outcomes has led to increased interest in using machine learning approaches to predict the success of crowdfunding efforts. By analyzing historical data, Machine Learning models can extract patterns and identify key features that influence campaign performance, such as category, funding goal, duration, launch date, and creator track record. Recent studies also emphasize the importance of textual and visual content, social network dynamics, and campaign updates as predictive factors [2].

This study aims to investigate the most influential factors contributing to the success of Kickstarter campaigns and assess the performance of various machine learning algorithms in predicting campaign outcomes. The models evaluated include traditional classifiers such as Decision Trees, Logistic Regression, and Support Vector Machines (SVM); ensemble-based methods like Random Forest, XGBoost, LightGBM, and Stacking Ensemble Learning; as well as deep learning approaches using Multi-layer Perceptron (MLP).

For experimentation, the study utilizes a publicly available dataset from Kaggle containing Kickstarter project data between June 15, 2009, and February 1, 2017. The analysis focuses only on finalized campaigns, either successful or failed, excluding live and suspended projects to ensure data integrity. The objective is to determine which model delivers the highest accuracy and robustness, while also offering practical insights for campaign creators and contributing to the broader field of crowdfunding analytics.

II. Literature Review

A. Overview of Crowdfunding and Kickstarter

Crowdfunding has emerged as a transformative tool in modern financing, enabling entrepreneurs, artists, and organizations to gather financial support directly from a large pool of backers, primarily via internet platforms. Allowing individuals and organizations to fund projects by collecting small contributions from a large number of people through online platforms. This decentralized model of fundraising reduces dependency on traditional financial institutions and provides an opportunity for creators to test market interest at an early stage [3].

Kickstarter stands out from the other crowdfunding platforms because of its all-or-nothing financing strategy, which only gives money to campaigns to reach or surpass their funding target. Although this strategy promotes artists' accountability and dedication, it also creates uncertainty because, regardless of the amount promised, if the goal is not met, there will be no funding [4]. Even with the popularity of the platform and the sheer volume of projects that are started each year, Kickstarter campaigns continue to have a low success rate. Unrealistic funding targets, poor marketing tactics, or a lack of supporter trust are the main causes of campaign failure[5].

Because of this unpredictability, there is interest in applying computational techniques, especially machine learning, to comprehend and forecast the factors that influence a campaign's success or failure. Scholars contend that the enormous volume of data produced by crowdfunding sites presents abundant chances to simulate campaign dynamics and give campaign creators useful insights[6].

B. *Ensemble and Stacking Learning*

In machine learning, ensemble learning refers to a technique that merges the predictions of several models to enhance overall accuracy, robustness, and generalization performance. This technique has proven effective across various domains, including image recognition, financial analysis, and social prediction tasks such as crowdfunding campaign outcomes [9].

The three most common ensemble techniques are bagging, boosting, and stacking. Bagging, as implemented in models like Random Forest, combines multiple weak learners in parallel to reduce variance. Boosting, used in algorithms such as XGBoost and LightGBM, builds models sequentially to minimize bias. Stacking (or stacked generalization) merges the predictions of multiple base models using a meta-learner that is trained to capture the error patterns of the base models.

Due to its capacity to combine the advantages of several models (such as neural networks and tree-based algorithms), Stacking has grown in prominence and frequently produces noticeably better predicted results than any one model alone. Because stacking can handle complicated and heterogeneous data, recent studies have demonstrated that it can be very useful in binary classification tasks, such as predicting the success of Kickstarter campaigns [10].

But there are drawbacks to stacking as well, like the possibility of overfitting if cross-validation is not used properly, as well as higher computing costs and model complexity. Therefore, when using this ensemble technique, it is crucial to take into account the trade-offs between resource needs and performance improvements.

C. *Previous Work in Kickstarter Funding Success Prediction*

Several recent studies have explored the use of tree-based and statistical machine learning models to predict the success of Kickstarter campaigns. A study by Lysin (2024) evaluated feature importance and the performance of Random Forest, XGBoost, and LightGBM on a dataset of over 150,000 projects from 2009–2018. The study found that campaign duration, subcategory, and funding goal were the most influential features, with Random Forest achieving the highest accuracy of 88.27% [11].

Similarly, Abrar et al. (2024) compared various machine learning models, including Logistic Regression, SVM, LDA, QDA, and tuned Decision Trees and identified Decision Trees with GridSearchCV as the top-performing model, achieving up to 99.86% accuracy, precision, and recall [12].

Patil et al. (2021) explored the application of deep learning techniques, particularly Multi-Layer Perceptron (MLP), for predicting the success of Kickstarter campaigns. Mehta et al. (2023) employed several Kickstarter-related datasets General (300,000+ rows), Content (18,100+), Description (379,000+), and Rewards (46,000+) to classify projects into "successful" or "failed" categories using deep learning architectures .

Each model consisted of an input layer (with neurons matching the number of features in each dataset), a hidden layer of the same size, and a single-neuron output layer. Among all algorithms tested, MLP achieved the highest predictive performance on the Description dataset (63.05%) and Rewards dataset (67.96%), outperforming other models such as KNN and Logistic Regression. These findings demonstrate the capability of MLP to model non-linear relationships in textual and structured data, making it a promising approach for success prediction in crowdfunding platforms.[13]

III. METHODOLOGY

This chapter describes the materials and methods utilized to compare the performance of each model architecture in classifying Kickstarter funding success. The methodology involves selecting a suitable dataset, preparing the dataset through preprocessing, and selecting the best models designed for stacking.

A. *Dataset*

The analysis in this study is based on data from, "The Kickstarter Campaigns dataset", sourced from the official Kaggle platform. Curated by Rachel Downs and Muhammad Ghuari as part of a Management Information Systems course at the University of Texas at Austin, it includes 68 qualities and 20,632 campaign records for initiatives that were started between June 15, 2009, and February 1, 2017.

TABLE. I. Data Description

Attributes	Description
Goal	The amount of money the creator wants to raise for the project
Category	The category of project
Country	The country where the project was launched.
Currency	The currency used for funding
Launch to deadline days	The duration between the project's launch date and its funding deadline.
State	The final status of the project
Blurb	Short description of project

The attributes mentioned in Table I are the selected attributes that will be used for modelling. The State variable is the target that will be used to predict the final status of a project. The selected attributes Goal, Category, Country, Currency, Launch to deadline days, and Blurb will be used to estimate whether a project will succeed or fail based on its characteristics. The reasoning behind the selection of these specific variables will be further discussed in the Exploratory Data Analysis (EDA) section.

B. Exploratory Data Analysis

The target variable Successful in the dataset shows a clear imbalance between the two classes. There are 14,614 projects (about 70.8%) labeled as unsuccessful, while only 6,018 projects (around 29.2%) are marked as successful. This means the data is heavily skewed toward unsuccessful projects, which could cause the model to favor predicting failure more often than success, leading to biased or less accurate results. Therefore, techniques like resampling, adjusting class weights, or using advanced models may be needed to improve prediction accuracy and ensure both classes are treated fairly.

Fig. 1. Imbalance Graph

Based on the correlation matrix as shown in Table. II with the target variable State, the selected attributes for modeling are Goal, Category, Country, Currency, Launch to deadline days, and Blurb. These features are considered relevant and available prior to the launch of a Kickstarter campaign, making them suitable for predictive analysis. Although usd pledged and backers count show a strong correlation with the target variable, they are not included in the model. In real-world use, these values are not known at the start of a campaign, so including them would not fit the purpose of the prediction model.

TABLE. II. Correlation with Target

Attributes	**Correlation**
usd_pledge	0.232241
pledge	0.224826
backers_count	0.194122
name_len	0.133414
name_len_clean	0.133032
TOPCOUNTRY	0.108490
USorGB	0.108420
launch_to_state_change_days	0.065503
blurb_len_clean	0.060587
static_usd_rate	0.059260
LaunchedTuesday	0.039861
state_changed_at_month	0.029588
deadline_month	0.025649
blurb_len	0.021875
create_to_launch_days	0.012799
launched_at_month	0.010042
created_at_hr	0.008278
state_changed_at_hr	0.005708
created_at_day	-0.000470
deadline_hr	-0.001228
launched_at_day	-0.008251
state_changed_at_day	-0.008285
created_at_month	-0.008615
deadline_day	-0.011189
id	-0.015477
DeadlineWeekend	-0.030578
goal	-0.035045
launched_at_hr	-0.054318
created_at_yr	-0.078833
launched_at_yr	-0.080460
state_changed_at_yr	-0.082565
deadline_yr	-0.086247
launch_to_deadline_days	-0.112968

The target variable shows low correlations with most variables, suggesting that its outcome likely depends on a combination of multiple factors rather than a single one.

C. Data Preprocessing

The data was split 80% for training and 20% for testing., where 20% was utilized to assess model performance on unseen data and 80% was used for training. This guarantees the model's successful generalization. Stratified k-fold cross-validation was used to increase the evaluation's robustness. This technique, which is essential for unbalanced datasets like Kickstarter campaigns, divides the data into k folds while maintaining the original class distribution. To offer accurate performance data, each fold is used k-1 times for training and once for testing. The results are then averaged. Across all dimensions, stratification guarantees fair representation of both successful and unsuccessful efforts.

Additionally, an NLP-based feature extraction step was applied. The blurb (short project description) was transformed into a readability score using the Gunning Fog Index via the textstat Python library. This index approximates the level of formal education required to comprehend the text upon first reading. Higher values reflect greater text complexity, potentially affecting a campaign's attractiveness and ease of understanding. Flesch Reading Ease was calculated using the textstat library to assess text readability; higher scores indicate simpler, more accessible language that can enhance a campaign's message clarity.

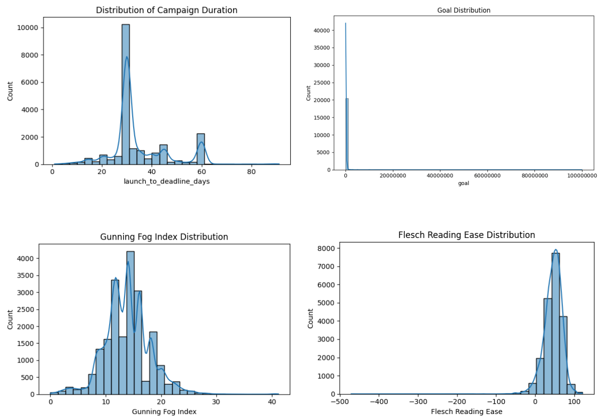

Fig. 2. Numerical Data's Distribution

To ensure data quality and consistency, several preprocessing steps were applied. Incomplete entries were either removed to prevent data leakage or bias. Next, categorical variables (e.g., Country, Category) were transformed using one-hot encoding to make them usable for machine learning algorithms. Considering the distribution of the numerical data as shown in Fig. 2, the numerical features were standardized to ensure a consistent scale across the dataset. The data were also balanced using SMOTE. It works by randomly increasing the number of minority class examples to achieve a balanced distribution.

This textual readability metric was included as a numerical feature, providing further insight into how the language used in campaign descriptions may correlate with success.

The final set of features used in our model are:

- goal
- launch_to_deadline_days
- SuccessfulBool
- gunning_fox_index
- flesch_reading_ease
- category (Apps, Blues, Comedy, Experimental, Festivals, Flight, Gadgets, Hardware, Immersive, Makerspaces, Musical, Places, Plays, Restaurants, Robots, Shorts, Software, Sound, Spaces, Thrillers, Wearables, Web, and Webseries)
- country (AU, BE, CA, CH, DE, DK, ES, FR, GB, HK, IE, IT, LU, MX, NL, NO, NZ, SE, SG, and US)
- currency (CAD, CHF, DKK, EUR, GBP, HKD, MXN, NOK, NZD, SEK, SGD, and USD).

D. *Modelling*

This study employs various machine learning models with distinct strengths. Logistic Regression is a simple binary classifier that uses a sigmoid function to estimate probabilities and interpret feature impact. Decision Tree models split data based on feature values and are easy to understand but prone to overfitting. Random Forest reduces overfitting by combining multiple trees trained on random subsets of the data. XGBoost and LightGBM are gradient boosting methods that build trees sequentially to correct errors, with LightGBM optimized for speed and memory efficiency. Support Vector Machine separates classes using an optimal hyperplane and handles non-linear data through kernel functions, though it can be slow on large datasets. Multilayer Perceptron is a neural network capable of capturing complex patterns but requires careful tuning. Lastly, Ensemble Learning combines XGBoost, LightGBM, and MLP as base models with Random Forest as a meta-learner to enhance overall performance.

E. *Model Evaluation*

Model training adhered to a standard evaluation procedure. First, to guarantee a balanced class distribution across folds, the dataset was divided using stratified k-fold cross-validation. Second, to mitigate class imbalance, SMOTE was used on every training fold. Lastly, to ensure proper normalization without distorting distributions, numerical features like goal, launch_to_deadline_days, Gunning Fog Index, Flesch Reading Ease were scaled using either StandardScaler or MinMaxScaler, depending on skewness.

Each model's performance was evaluated using accuracy, recall, precision, F1-score, MSE, and confusion matrices after training and testing across all folds. To visualize the prediction patterns more clearly, the results were presented using heatmaps.

TABLE. III. Model Evaluation

Model	Precision	Accuracy	Recall	F1 Score	AUC
Decision Tree	0.60	0.67	0.61	0.60	0.606
Random Forest	0.65	0.71	0.63	0.64	0.728
Logistic Regression	0.66	0.73	0.62	0.63	0.731
SVM	0.69	0.71	0.71	0.69	0.711
MLP	0.70	0.72	0.72	0.71	0.738
XGBoost	0.73	0.74	0.74	0.73	0.771
LightGBM	0.73	0.74	0.74	0.74	0.777

These assessments led to the selection of MLP, LightGBM, and XGBoost as base learners in a stacked ensemble architecture. Random Forest was selected as the meta-learner because of its balanced scores and reliable generalization capacity. By combining the advantages of top-performing models and reducing their particular shortcomings, this ensemble approach sought to enhance generalization and predictive performance.

TABLE. IV. Stacking Model Evaluation

Model	Precision	Accuracy	Recall	F1 Score	AUC
Stacking	0.67	0.54	0.54	0.56	0.738

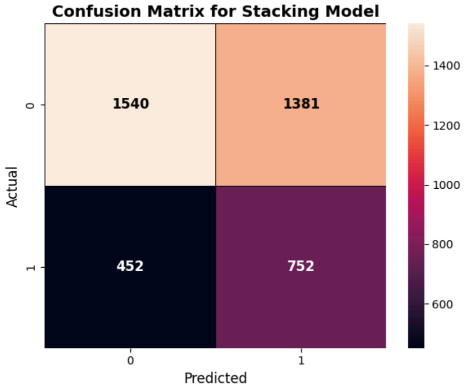

Fig. 3. Confusion Matrix

Fig. 3 shows that the model was able to correctly recognize 1,540 negative cases and 752 positive cases. However, it also made several mistakes 1,381 negative cases were incorrectly labeled as positive, and 452 positive cases were missed and labeled as negative. This suggests that while the model does a fairly good job at identifying negative cases, it has more difficulty accurately detecting positive ones, as reflected in the higher number of misclassifications.

IV. Results and Discussions

These outcomes demonstrate how well the models were able to forecast Kickstarter campaign outcomes. With an accuracy of 0.74, balanced precision and recall of 0.73 and 0.74, an F1 Score of 0.74, and the greatest AUC of 0.777, LightGBM was the best-performing individual model out of all of them. It is very dependable for binary classification jobs since it shows both good classification performance and well-calibrated probability outputs.

A strong complementary model, XGBoost came in second with comparable accuracy 0.74, precision 0.73, and recall 0.74, but a little lower F1 Score 0.73 and AUC 0.771. MLP also performed well overall, exhibiting its deep learning potential for identifying non-linear patterns with a slightly lower accuracy of 0.72 and AUC of 0.738, but a steady F1 Score and precision of 0.71 and 0.70, respectively.

A stacked ensemble technique was created to make use of these high-performing models' complementary strengths. Because of their exceptional individual results, XGBoost, LightGBM, and MLP were selected as the basis learners in this setup. Because of its strong balance across evaluation criteria and resilience to overfitting, Random Forest was chosen as the meta-learner.

The stacked ensemble's initial testing revealed a significant loss in overall performance. Although the average accuracy is low, the stacking model can learn general patterns from different base learners, thus making it more generalized. This helps when the model is faced with out-of-distribution data.

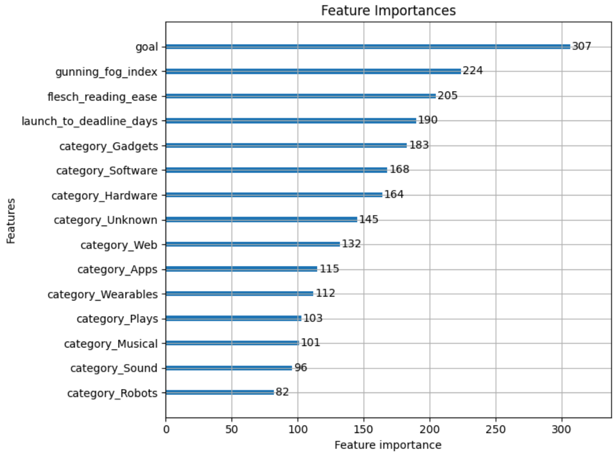

Fig. 4. Top 15 Feature importances

The importance was taken from the LightGBM model. It is measured by how often a feature is used to split the data or how much it improves the prediction. The more useful a feature is, the higher its importance. From Fig. 4 the most important feature is goal, with a feature importance score of 307. This suggests that the fundraising goal plays a crucial role in determining project outcomes. gunning_fog_index and flesch_reading_ease are also top feature importances, which means that how easy or complex the text is plays a big role in predicting success. launch_to_deadline_days This is the duration of the campaign, the duration of the campaign likely affects whether a project gets funded, possibly because longer campaigns perform differently. Category-related features like category_Gadgets, category_Software show their importance means that the campaign's category significantly influences success. For example, tech-related projects might behave differently from music or the arts.

In short, how the campaign is written, how long it runs, and what type of project it is are very important in predicting success.

V. Conclusion

Among all the models tested, LightGBM and XGBoost performed the best in terms of accuracy and AUC scores during cross-validation. However, even though these models had strong results in cross-validation, the stacked ensemble model, which combines XGBoost, LightGBM, and MLP with a Random Forest meta-learner, showed better performance on real user data. This shows that ensemble techniques can capture complex patterns that one model alone might miss. Our research also recognizes some limitations, such as the stack model performing worse in cross-validation, possibly due to overfitting or the impact of specific data splits. The dataset used may not fully represent real-world scenarios, and the lack of extensive hyperparameter tuning limits the models' generalizability.

Moving forward, this study will focus on improving the stack model by fine-tuning the hyperparameters, trying different meta-learners, and adding more relevant features or external datasets to make the model more reliable and adaptable to real-world situations. Additionally, a web application will be developed that will allow users to easily interact with the model and utilize it for real-time predictions. Future research should focus to extend the model to predict not only the success state but also the approximate USD pledge amount and the backer count.

Author's Contribution

Y.J.W. was responsible for conceptualizing the study, setting its direction, and served as the primary author of the manuscript. M.A.A. carried out the experiments and contributed to the writing process. A.A.S.G. and R.C.P. supervised the research and provided ongoing guidance throughout the project. All authors have reviewed and approved the final manuscript.

Availability Data and Materials

The Kickstarter Campaigns dataset used in this study is publicly available on https://www.kaggle.com/datasets/sripaadsrinivasan/kickstarter-campaigns-dataset.

All associated code has also been made publicly available on Google Colab https://colab.research.google.com/drive/14AzFxbzTTaFOjAXk2ZwpKb2oUDGEikJA#scrollTo=5BKTfUuFajhZ

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