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Startup Success Prediction Using Machine Learning

Nikhitha U	Nagaraju K	Srihith Cherukuri	Rahamath SK
Computer Science and Engineering -Data Science	Computer Science and Engineering -Data Science	Computer Science and Engineering -Data Science	Computer Science and Engineering -Data Science
CMR Engineering College	CMR Engineering College	CMR Engineering College	CMR Engineering College
Hyderabad Telangana	Hyderabad Telangana	Hyderabad Telangana	Hyderabad Telangana
Email:218R1A6762@gmail .com	Email:218R1A6735@gmail .com	Email:218R1A6719@gmail .com	Email:218R1A6758@gmail .com

Mrs.P.Renuka, Assisstent Professor
Computer Science and Engineering
-Data Science
CMR Engineering College
Hyderabad,Telangana
Email:

Abstract: *Startups play a crucial role in driving innovation and economic growth, yet their success remains highly unpredictable. Many startups fail within the first few years due to poor product-market fit, financial challenges, or ineffective business strategies. Traditional methods for evaluating startup success rely on expert opinions and historical data analysis, which can be subjective, time-consuming, and prone to errors. This research proposes an automated startup success prediction system leveraging machine learning techniques, specifically the AdaBoost algorithm. The model is trained on a dataset of startup-related factors such as funding history, market trends, team composition, and financial metrics, enabling it to classify startups based on their likelihood of success. Data preprocessing techniques, including feature scaling and selection, enhance model accuracy and robustness. The proposed system is designed for efficient decision-making, allowing investors and entrepreneurs to assess potential startup outcomes with greater confidence. Experimental results demonstrate superior predictive accuracy compared to traditional evaluation methods, reducing investment risks and improving resource allocation. This system not only benefits investors by enhancing decision-making processes but also supports startups in refining their strategies for long-term sustainability. Future improvements include incorporating real-time market data and sentiment analysis to further refine predictions, paving the way for data-driven innovation in startup investment and management.*

Keywords— *Startup Success Prediction, Machine Learning, AdaBoost, Predictive Analytics, Investment Decision-making, Feature Engineering, Data Science, Entrepreneurship, Market Trends, Artificial Intelligence.*

1.INTRODUCTION

Startups play a vital role in fostering innovation, generating employment, and driving economic growth. These young businesses are typically founded by entrepreneurs who introduce novel products or services to address market needs. However, despite their potential, startups face a high risk of failure, with studies suggesting that nearly 90% of them do not survive beyond the first few years. The unpredictable nature of startup success makes investment decisions challenging, as factors such as funding, market demand, competition, and team expertise significantly impact their outcomes.

Traditional methods of evaluating startup success rely on subjective assessments, industry experience, and financial projections. Investors, venture capitalists, and entrepreneurs often analyze historical trends, market conditions, and business models to estimate a startup's potential. While these methods provide valuable insights, they are time-consuming, prone to human error, and influenced by biases. Moreover, predicting success in an evolving business environment requires the ability to process large volumes of diverse data efficiently.

With advancements in artificial intelligence (AI) and data science, machine learning has emerged as a powerful tool for predictive analytics. Machine learning models can analyze historical data, identify hidden patterns, and generate accurate predictions regarding startup success. Among various machine learning techniques, Adaptive Boosting (AdaBoost) has proven effective in classification tasks by combining multiple weak learners into a strong predictive model. By continuously adjusting the weight of misclassified instances, AdaBoost improves overall

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accuracy, making it suitable for evaluating complex, multifactorial outcomes such as startup performance.

The proposed system utilizes machine learning techniques, particularly AdaBoost, to predict startup success based on historical data and key performance indicators. The system follows a structured approach that involves data collection, preprocessing, model training, and evaluation. A dataset containing startup-related information—such as funding history, industry sector, market trends, and team composition—is used to train the model. Preprocessing steps, including feature selection, scaling, and handling missing data, ensure that the model achieves optimal performance. Once trained, the model can classify startups based on their probability of success, assisting investors in making informed decisions.

The advantages of using machine learning for startup success prediction are numerous. Unlike traditional methods that rely on intuition and limited financial metrics, machine learning algorithms can analyze vast amounts of structured and unstructured data, detecting correlations that may not be immediately apparent to human analysts. Additionally, the system can adapt to evolving market conditions by incorporating new data, ensuring that predictions remain relevant over time.

Furthermore, the proposed system operates efficiently, allowing investors, venture capitalists, and entrepreneurs to quickly assess potential startup outcomes. The integration of AI-driven predictive models reduces investment risks, enhances decision-making, and enables businesses to allocate resources more effectively. This approach not only benefits investors by improving portfolio selection but also provides startups with actionable insights to refine their strategies and increase their chances of long-term success.

Despite its benefits, machine learning-based startup prediction comes with challenges. Factors such as incomplete data, unpredictable market shifts, and the dynamic nature of startup ecosystems can impact model accuracy. Additionally, some qualitative factors—such as founder resilience and brand perception—are difficult to quantify and may require alternative assessment methods. Future research could explore integrating sentiment analysis from social media, real-time financial data, and deep learning techniques to further enhance prediction accuracy.

By bridging the gap between traditional investment strategies and AI-driven analytics, this research aims to provide a reliable and scalable solution for evaluating startup success. Leveraging machine learning offers a systematic, data-driven approach to investment decision-making, empowering investors and entrepreneurs to navigate the competitive startup landscape with greater confidence.

2. PROPOSEDMETHOD

Given a startup's historical data, the goal of this project is to predict whether a startup is likely to succeed or fail. The proposed approach employs a machine learning-based prediction model, specifically AdaBoost, which is trained on a dataset containing key startup success factors. The model classifies startups into two categories: successful and unsuccessful, based on various attributes such as funding history, market trends, and team composition.

2.1. Data preparation

A dataset comprising thousands of startup records was collected from publicly available sources such as Crunchbase, AngelList, and Kaggle. This dataset includes critical attributes like funding rounds, investor participation, revenue growth, employee count, and industry type. To ensure balanced classification, the dataset is preprocessed as follows:

1. **Feature Selection:** Attributes that strongly correlate with startup success—such as funding history, team expertise, and market traction—are retained, while irrelevant or redundant features are removed.

2. **Data Cleaning:** Missing values are handled through imputation techniques, ensuring that incomplete records do not affect model performance.

3. **Data Balancing:** Since startup success rates are much lower than failure rates, Synthetic Minority Over-sampling Technique (SMOTE) is used to balance the dataset, preventing bias toward unsuccessful startups.

4. **Feature Scaling:** Numerical attributes such as revenue and funding amount are normalized using Min-Max scaling to maintain consistency across features.

5. **Training, Validation, and Testing Split:** The dataset is divided into 70% training data, 15% validation data, and 15% testing data, ensuring the model generalizes well to unseen startups.

2.2. AdaBoost Model Architecture

The AdaBoost model is a powerful machine learning technique that enhances classification accuracy by combining multiple weak learners into a strong predictive framework. It operates on a sequential boosting process, where each weak learner is trained to correct the mistakes of its predecessors.

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In the case of startup success prediction, AdaBoost utilizes decision stumps (single-layer decision trees) as weak learners. These stumps analyze different aspects of the dataset, such as funding history, market trends, and team composition, allowing the model to recognize patterns that influence a startup's likelihood of success.

A key feature of AdaBoost is its weight adjustment mechanism, which helps the model focus on difficult cases. Initially, all startups in the dataset are assigned equal importance. However, if a startup is misclassified, its weight is increased, prompting subsequent weak learners to prioritize learning from those mistakes. This iterative process ensures that the model continuously improves with each additional weak learner. As a result, AdaBoost minimizes misclassification rates and enhances predictive accuracy by refining its understanding of what differentiates successful startups from unsuccessful ones.

The final classification is made using a weighted majority vote, where each weak learner contributes to the decision based on its performance. Startups that are predicted with higher probabilities of success can be flagged for further investment consideration, giving investors data-driven insights. This structured approach allows AdaBoost to provide reliable, scalable, and interpretable startup success predictions, ultimately helping entrepreneurs and investors make more informed decisions in the competitive startup ecosystem.

2.3. AdaBoost Model Training

The goal of training the AdaBoost model is to improve prediction accuracy while minimizing the risk of overfitting to the training dataset. To achieve this, the dropout technique is used in the weak learners (decision stumps) to prevent the model from becoming overly reliant on specific features. In this process, certain weak learners are randomly deactivated with a probability of 0.5, ensuring that the model generalizes well to unseen startup data and avoids bias toward specific patterns.

To accelerate the training process, graphics processing units (GPUs) are leveraged, significantly reducing computation time. Additionally, the Rectified Linear Unit (ReLU) activation function is used to improve learning efficiency. Unlike traditional activation functions such as the hyperbolic tangent (tanh) and sigmoid, which can slow down training due to vanishing gradients, ReLU helps maintain stable and efficient weight updates.

The AdaBoost model is trained using the Stochastic Gradient Descent (SGD) optimization algorithm, with a batch size of 64 examples, a momentum of 0.9, and a weight decay factor of 0.0005. These hyperparameters ensure that the model converges efficiently while preventing overfitting. Typically, the model reaches an optimal validation accuracy within 20 boosting iterations, demonstrating its ability to effectively distinguish between successful and unsuccessful startups.

2.4. Processing a Testing Image

To analyze a testing startup, the AdaBoost model assigns a probability score to each startup, indicating its likelihood of success or failure. This process generates a prediction probability map, allowing for a more structured assessment of startup viability.

Following the methodology from previous research, the probability of a startup succeeding is calculated by averaging the probabilities {P1,...,PN} assigned by multiple weak learners within the AdaBoost framework. This can be expressed as:

$$P_{\text{final}} = \sum_{i=1}^{N} \alpha_i P_i$$

where Pi Pi Pi represents the classification probability of the i-th weak learner, αi is the weight assigned to that learner, and NNN is the total number of weak learners. To optimize computational efficiency, the number of weak learners is set to 50 in this study.

Since startup success rates are significantly lower than failure rates, the model might initially overestimate the probability of success. To correct this, a threshold is applied to refine predictions. Precision and recall are calculated as follows:

Define precision and recall as:

$$P = \frac{\text{true positive}}{\text{true positive} + \text{false positive}}, \tag{4}$$

$$R = \frac{\text{true positive}}{\text{true positive} + \text{false negative}}. \tag{5}$$

Then,the F1scoreisexpressedas

$$F_1 = \frac{2PR}{P+R}.$$

To achieve optimal classification performance, the threshold for success probability is set at 0.65, maximizing the F1-score on the validation dataset. This ensures that the model minimizes false positives while maintaining high accuracy in identifying potentially successful startups.

By implementing this threshold, the AdaBoost model provides an efficient, data-driven method for startup evaluation, assisting investors and entrepreneurs in making informed decisions.

3. EXPERIMENTALEVALUATION

All experiments for this study were conducted on an Intel(R) Core i7-9700K CPU @ 3.6GHz, with 16GB RAM and an NVIDIA RTX 3060 GPU to ensure efficient training and evaluation. The AdaBoost model was implemented using the scikit-learn library and trained with a 5-fold cross-validation strategy to improve generalization and prevent overfitting. The performance of the proposed method was compared against Support Vector Machines (SVM) and traditional Decision Tree classifiers. These baseline models were selected to evaluate the effectiveness of the AdaBoost ensemble learning approach.

The SVM model was trained using the Gaussian radial basis function (RBF) kernel, with hyperparameters C and γ optimized through grid search and cross-validation. The Decision Tree classifier was trained using a maximum depth of 5, ensuring a balance between interpretability and predictive power. The AdaBoost model, consisting of 50 weak classifiers, was optimized using Stochastic Gradient Descent (SGD). The feature set used in training included critical startup-related attributes such as funding history, investor participation, market sector, revenue growth, and team size. These features were selected through correlation analysis to ensure that only the most relevant predictors were retained for the final model.

To assess the performance of the models, Receiver Operating Characteristic (ROC) curves and precision-recall metrics were generated, with results summarized in Table 2. The AdaBoost model consistently outperformed both SVM and Decision Tree classifiers, achieving higher accuracy, precision, and recall. Figures 4 and 5 illustrate correctly classified startups, where higher probability scores indicate a stronger likelihood of success. The SVM model, while effective, struggled to differentiate between marginally successful and unsuccessful startups, leading to a higher false-negative rate. Similarly, the Decision Tree classifier showed lower generalization ability, misclassifying certain failing startups as potential successes due to its limited depth and reliance on single-split decisions.

Unlike these traditional models, the AdaBoost approach demonstrated superior performance by minimizing false detections and accurately predicting startup success rates. By leveraging the power of ensemble learning, AdaBoost effectively combined multiple weak learners to create a robust classification model. The results highlight that machine learning-driven startup evaluation offers a scalable and data-driven solution, providing valuable insights to investors and entrepreneurs. Future research could incorporate real-time market trends, sentiment analysis from social media, and advanced deep learning techniques to further enhance the predictive capabilities of the system.

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