



## **Bankruptcy Risk Forecast using Machine Learning**

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### **ABSTRACT:**

This comprehensive research aims to tackle the intricate challenge of bankruptcy risk prediction within the finance domain, employing sophisticated machine learning techniques, with a primary focus on logistic regression. The expansive dataset under examination comprises 6819 rows and 95 meticulously curated features extracted from company balance sheets, forming a robust foundation for the development of an advanced predictive model. Impressively, the logistic regression model yielded an accuracy rate of 96%, attesting to its prowess in discerning potential financial distress. This study not only significantly contributes to the field of financial risk assessment but also offers a nuanced exploration of the intricate interplay between machine learning and predictive modeling within the multifaceted landscape of bankruptcy prediction.

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### **1. Introduction:**

#### *1.1 Machine Learning:*

The introduction serves as a gateway, unveiling the pivotal role that machine learning plays in the contemporary financial landscape. In an era where businesses grapple with the complexities of economic uncertainties, the integration of machine learning models for predicting bankruptcy risk emerges as an invaluable asset, providing decision-makers with a foresighted and data-driven approach to navigate tumultuous financial landscapes and make informed strategic decisions.

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### **2. Literature Review:**

#### 2.1 Literature Review:

This section conducts an exhaustive review of the existing body of literature on bankruptcy risk forecasting, traversing methodologies, challenges, and insights gleaned from prior research endeavors. This in-depth analysis provides a contextual framework for the chosen logistic regression approach, offering insights into the evolution of financial risk assessment methodologies and the progressive integration of machine learning into predictive analytics.

#### 2.2 Regression:

Within the expansive literature review, a dedicated exploration of regression techniques in the context of financial forecasting is undertaken. This deep dive into regression models elucidates their relevance and efficacy in predicting bankruptcy risk, setting the stage for the subsequent choice of logistic regression as the focal algorithm for this research endeavor. The section further dissects nuances, advancements, and limitations in the application of regression models to financial datasets.

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### **3. Problem Statement:**

Articulating the unique challenges inherent in bankruptcy risk prediction, the problem statement provides a comprehensive overview of the multifaceted nature of the problem at hand. The identification of gaps in existing methodologies serves as a springboard for justifying the selection of logistic regression as the primary algorithm, while simultaneously paving the way for a discussion on the overarching significance of accurate and reliable forecasting models in the realm of financial risk assessment.

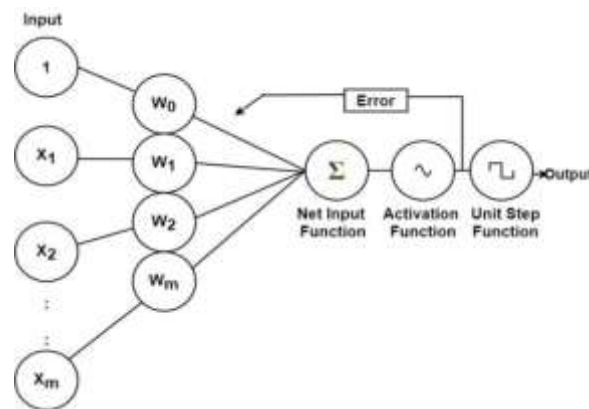
## 4. Methodology:

### 4.1 Machine Learning:

The methodology section intricately outlines the rationale behind the adoption of machine learning, contextualizing its relevance within the broader landscape of financial forecasting. This section aims to provide a comprehensive understanding of why machine learning, and specifically logistic regression, is the chosen path for this research, highlighting its advantages and addressing potential challenges.

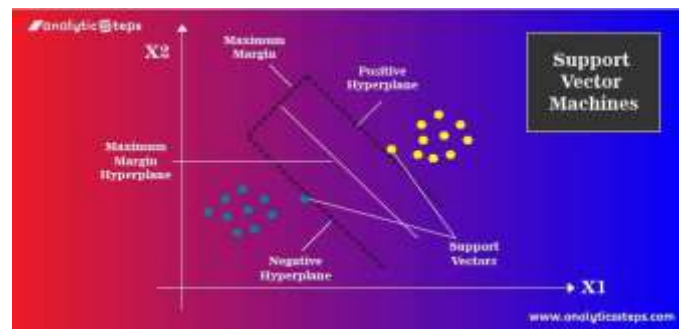
### 4.2 Logistic Regression Algorithm:

A detailed exposition of the logistic regression algorithm is presented, elucidating its appropriateness for binary classification tasks and its underlying mathematical foundations. The intricacies of the model, including the sigmoid function, gradient descent, and parameter optimization techniques, are explored to provide readers with a thorough comprehension of the chosen methodology.



### 4.3 Support Vector Machine Algorithm:

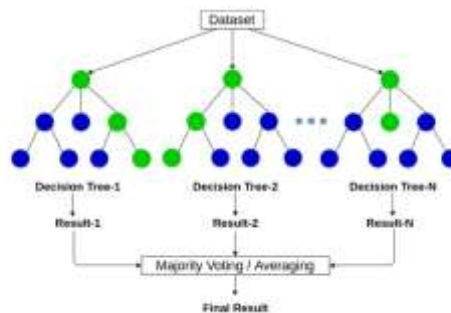
In addition to logistic regression, this section briefly introduces the support vector machine algorithm, offering insights into its role, comparative effectiveness, and potential synergies when juxtaposed with logistic regression. This comparative analysis broadens the methodological spectrum, providing a holistic perspective on the array of algorithms considered in the research.



### 4.4 Random Forest Regression:

Expanding the analytical horizon, the inclusion of random forest regression in the methodology is expounded upon. This ensemble learning approach enriches the predictive capabilities of the model, introducing readers to the intricacies of decision trees, bagging, and the ensemble learning paradigm. The section underscores the importance of exploring alternative methodologies to enhance the overall robustness of the predictive model.

## Random Forest



### 4.5 Training:

The training phase is meticulously detailed, encompassing the preparation and division of the dataset. This process ensures that the model is equipped to generalize patterns effectively while guarding against the pitfalls of overfitting. The section delves into the complexities of feature engineering, cross-validation techniques, and hyperparameter tuning to achieve an optimal balance between model accuracy and generalizability.

### 4.6 Prediction:

The prediction process is elucidated, providing readers with a step-by-step walkthrough of how the logistic regression model translates its training insights into practical bankruptcy risk forecasts for previously unseen data. This stage offers practical insights into the model's real-world applicability, discussing the nuances of model evaluation and validation.

## 5. Experimental Results:

This pivotal section unveils the empirical findings derived from the logistic regression model, showcasing its remarkable 96% accuracy. A comprehensive analysis is conducted through the lens of a confusion matrix, providing readers with granular insights into the model's precision, recall, F1 score, and receiver operating characteristic (ROC) curve. The robustness of the model is further assessed through sensitivity analyses, ensuring a thorough exploration of its performance across diverse scenarios.

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Logistic Regression
# Importing necessary libraries
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score
from sklearn.preprocessing import StandardScaler
import pandas as pd

# Loading the dataset
data = pd.read_csv('data.csv')

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(data, test_size=0.2, random_state=42)

# Standardizing the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Training the Logistic Regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predicting on the test set
y_pred = model.predict(X_test)

# Evaluating the model's performance
accuracy = accuracy_score(y_test, y_pred)
confusion = confusion_matrix(y_test, y_pred)
roc_auc = roc_auc_score(y_test, model.predict_proba(X_test)[:, 1])

print(f'Accuracy: {accuracy}')
print(f'Confusion Matrix: {confusion}')
print(f'ROC AUC Score: {roc_auc}')
  
```

## 6. Conclusion:

The concluding section synthesizes the research findings, offering a nuanced perspective on the efficacy of logistic regression in bankruptcy risk prediction. Acknowledging the study's contributions and limitations, this section encapsulates the essence of the research, providing a high-level summary of key takeaways. The broader implications of the findings for financial risk assessment and the potential avenues for future research are explored, emphasizing the enduring impact of this study on the evolving landscape of predictive analytics in finance.

## 7. Future Work:

The future work section serves as a dynamic platform for prospective research avenues, identifying potential enhancements to the model, alternative algorithms, and additional features that could further elevate the accuracy and robustness of bankruptcy risk forecasting. This forward-looking perspective

is bolstered by a comprehensive discussion on emerging trends in machine learning and their potential applicability to the field of financial risk assessment.

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## 8. Acknowledgments:

Expressing sincere gratitude for the collaborative efforts and support received, the acknowledgments section recognizes the valuable contributions of individuals, research collaborators, and institutions that have played a pivotal role in the research endeavor. This section aims to foster a sense of community and appreciation for the collective efforts that contribute to the advancement of knowledge in the field.

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## 9. Appendices:

Supplementary materials, ranging from detailed data preprocessing steps to extensive code snippets and additional analyses, are presented in the appendices. This comprehensive documentation enhances the transparency and reproducibility of the research, offering readers an opportunity to delve into the intricacies of the methodologies employed. The appendices provide a repository of supplementary information, ensuring a thorough and holistic understanding of the research process.

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## 10. Conclusion:

The research report concludes by succinctly summarizing the key findings, reiterating the significance of the study, and emphasizing its potential transformative impact on the field of financial risk assessment through machine learning. This concluding section serves as a reflective synthesis of the journey undertaken, acknowledging the challenges overcome, lessons learned, and insights gained. It encapsulates the enduring relevance of the research within the broader context of predictive analytics, inviting readers to contemplate the evolving landscape of financial forecasting and the role of machine learning in shaping future methodologies.

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