Comprehensive Journal of Science
Volume (10), Issue (37), (NOV. 2025)
SICST2025, www.sicst.ly
ISSN: 3014-6266

مجلة العلوم الشاملة
عدد خاص بالمؤتمر الدولي الثالث للعلوم والتقنية
المجلد (10)، العدد (37)، (نوفمبر2025)
ردمد: 3014-6266

# Machine learning techniques as an advanced hybrid framework for improving crisis management in investment sectors: an experimental study

**Mustafa krekshi [1*], and Dr Juma Ibrahim [2]**

[1] Postgraduate Department, Software Development Technology (CCTT), College of Computer Technology, Tripoli, Libya

[2] Postgraduate Department, Software Development Technology (CCTT), College of Computer Technology, Tripoli, Libya

*Corresponding author: MK2303006@cctt.edu.ly

*Corresponding author: juma.ibrahim@cctt.edu.ly

# تقنيات التعلم الالي من خلال اطار هجين متطور لتحسين ادرة الأزمات في القطعات الاستثمارية : دراسة تجريبية

**. مصطفى الكريكشي[1]، د. جمعة الضبيع [2]**

[1] الدراسات العليا، تقنية تطوير البرمجيات، كلية تقنيات الحاسوب، طرابلس، ليبيا

[2] الدراسات العليا، تقنية تطوير البرمجيات، كلية تقنيات الحاسوب، طرابلس، ليبيا

Received: 02-06-2023; Revised: 02-07-2023; Accepted: 17-07-2023; Published: 20-08-2023

## Abstract

Risk management is a fundamental element in today's vital investment sectors due to the growing scale and complexity of economic data. Evaluating business risks, plans, and timelines using traditional methods—including analytical, technical, and inferential models—has become insufficient for addressing the complex structures of modern datasets.

This study aims to develop a comparative hybrid framework that integrates machine learning techniques to enhance crisis management and reduce its impact on critical sectors such as financial investments, oil and gas fields, and real estate. The proposed framework employs linear regression, classification, and clustering, with a focus on the bias–variance trade-off to ensure an optimal balance between accuracy and generalization.

The study demonstrates how these techniques can be used to predict risks, detect patterns, and support strategic decision-making processes (before, during, and after crises) to mitigate crisis severity. The framework utilizes several evaluation metrics: classification performance is measured through accuracy, precision, and recall; regression performance is assessed using the root mean square error (RMSE); and clustering quality is evaluated using the Silhouette Score. Together, these .metrics provide a clear and balanced view of model performance and generalization capabilities

**Key words**

Artificial Intelligence Learning Techniques, Hybrid Framework, Machine Learning, Classification, A Model for Improving Crisis Management

إدارة المخاطر هي عنصر أساسي في قطاعات الاستثمار الحيوية اليوم بسبب اتساع وتعقيد البيانات المعنية في البيانات الاقتصادية، وتقييم مخاطر مواقف الأعمال والخطط والجداول الزمنية باستخدام طرق تقليدية تتضمن نماذج تحليلية وتقنية واستنتاجية غير كافٍ لمعالجة الهياكل المعقدة للبيانات الحديثة.

تهدف هذه الدراسة إلى تطوير إطار عمل هجين مقارن يجمع بين تقنيات التعلم الآلي لتعزيز إدارة الأزمات وتقليل تأثيرها في القطاعات الحيوية مثل الاستثمارات المالية، وحقول النفط والغاز، والعقارات. يعتمد الإطار المقترح على الانحدار الخطي، والتصنيف، والتجميع، مع التركيز على مشكلة التحيز مقابل التباين لضمان التوازن بين الدقة والتعميم.

توضح هذه الدراسة كيف يمكن استخدام هذه التقنيات للتنبؤ بالمخاطر، واكتشاف الأنماط، ودعم الإجراءات وعمليات القرار الاستراتيجي (قبل واثناء وبعد) للتخفيف من الأزمات. ، يستخدم الإطار عدة مقاييس تقييم؛ حيث تُقاس مهام التصنيف عبر الدقة، والدقة الإحصائية (Precision)، والاستدعاء (Recall)، بينما يُستخدم متوسط الجذر التربيعي للخطأ (RMSE) لقياس متوسط الانحراف في توقعات الانحدار، ويُستخدم مقياس السيلويت (Silhouette Score) لتقييم جودة نتائج التجميع. وتوفر هذه المقاييس مجتمعة صورة واضحة ومتوازنة عن أداء النماذج وقدرتها على التعميم.

**مصطلحات البحث:** تقنيات تعلم الذكاء الاصطناعي، إطار هجين، تعلم الآلة، التصنيف، نموذج لتحسين إدارة الأزمات

.

## Introduction

The landscape of risk management in the financial sector has undergone a significant transformation through the increasing integration of machine learning-based risk models (Mashrur et al., 2020). This paradigmatic shift indicates a radical change in the methodologies employed by financial institutions to manage risks and mitigate their impact, Predicting financial distress is a focal area in corporate finance and economics, representing a persistent challenge for investors, companies, and the broader economic system, often serving as an indicator of an impending crisis. Financial crisis prediction signals imminent challenges and has profound implications for maintaining shareholder capital, The potential of machine learning technologies to enhance risk forecasting has garnered significant attention, particularly focusing on measuring volatility and uncertainty (Ghani et al., 2022; Liang et al., 2020). This improvement carries substantial implications for managing the emerging risks inherent in financial assets. Investment, oil, gas, and real estate sectors face multiple risks such as market volatility, natural disasters, cyberattacks, and price fluctuations , Therefore ,The adoption of machine learning techniques has become a crucial tool for developing proactive systems that enable the prediction of potential problems and the implementation of appropriate preventive measures , This enhances decision-making capabilities for financial institutions, vital sectors, and investors' policies (Tien & Hung, 2022; Tripathy, 2022). Volatility, as proposed by Markowitz (1967), plays a pivotal role in risk evaluation within the oil, gas, real estate, and financial investment sectors, where accurate estimation of volatility is essential for evaluating financial derivatives and assessing investment portfolios

**Aims & Objectives**

**Objective**

The aim of publishing this paper at this conference is to develop an integrated risk management framework that supports effective decision-making for crisis .management in vital sectors

**Aims**

Build a univariate linear regression model as a baseline and apply classification .models to assess risk levels

Apply classification models to evaluate risk levels using clustering to categorize .similar scenarios

Measure the balance between bias and variance to improve predictive performance .and provide practical guidance for applying and analyzing the framework

**Problem Statement**

The absence of economic analysis models that accommodate investment sectors, along with the lack of capabilities to predict strategic crises, leads to weak response and planning, resulting in potential financial and human losses.

We aim to address this through the development of a framework for this model.

**Related Work**

The integration of artificial intelligence (AI) in financial market predictions has led to innovative solutions for forecasting stock prices, their volatility, and risks. This review highlights advancements in AI and machine learning (ML) in these areas.

Engel (1982) introduced a pioneering approach to estimating volatility, which was followed by Bollerslev (1986), an enhancement that can explain the persistent volatility in financial data. Over time, these models have been expanded and integrated with traditional techniques such as linear regression and regression using support vectors to improve predictions Many researchers in the oil industry have relied on machine learning and deep learning to predict the future based on past knowledge. Since our dataset is a type of continuous problem (time series), we had to delve deeper and explore the possibility of achieving high results with our dataset [1] The application of linear regression and LSTM in oil production forecasting uses Random Forest and Gradient Boosting to predict failures.

Financial distress prediction is a crucial area in finance and economics, aimed at identifying early warning signs of instability and financial crises in companies. The scientific literature often links the concept of financial distress.[14]The analyst's task is to select the ideal dataset using scientific methods alongside the expertise of the evaluators, and to integrate the research problem and the knowledge of the assessment object (evaluation goal) with an appropriate analytical tool [15

## Methodology

Predicting the impact of a specific economic or environmental factor on investment .or production performance through linear regression

Sorting potential risks into different levels (low, medium, high) through logistic .regression and classification

Aggregating crises or similar scenarios and identifying common patterns across .different sectors through clustering

Ensuring a balance in the models between good learning and the ability to generalize .to new data, also through bias analysis versus variance analysis

| Process | About the details |
|---|---|
| **Data Collection** | Approximately 925 training project databases and 250 test project databases were collected, along with a descriptive file detailing the variables |
| **Changes in the original data** | Changes in the original data: the data table includes project ID, sector, capital, revenues, costs, market volatility, risks, project duration, and risk level. |
| **Data processing** | This process is done by data evaluation, segment coding, and data partitioning for training and testing. |

## The models used and their application

| model | goal | features | Evaluation criteria | Results: |
|---|---|---|---|---|
| **Linear Regression Model** | : RMSE, $R^2$ Score | All digital and derived variables | One of the goals of designing this model was to predict the return on investment. | RMSE = 0.089, $R^2$ = 0.847 |
| **Logistic Regression Model** | Accuracy, F1-Score, Confusion Matrix | All digital and derived variables | There is a need to classify the level of risk (low, medium, high) | : Accuracy = 0.89, F1-Score = 0.87 |
| **K-Means Clustering Model** | 4 (مطابق لعدد القطاعات) | It is about the basic digital variables. | There is also a need to identify investment groups through Clustering. | These are 4 selected groups that are distinguished by success. |

## Evaluation Expected Contribution

### Evaluation

**The evaluation is done through a test using performance metrics (MAE, F1, classification accuracy).**

**Evaluation is also done by comparing individual models against the hybrid framework.**

### Expected Contribution

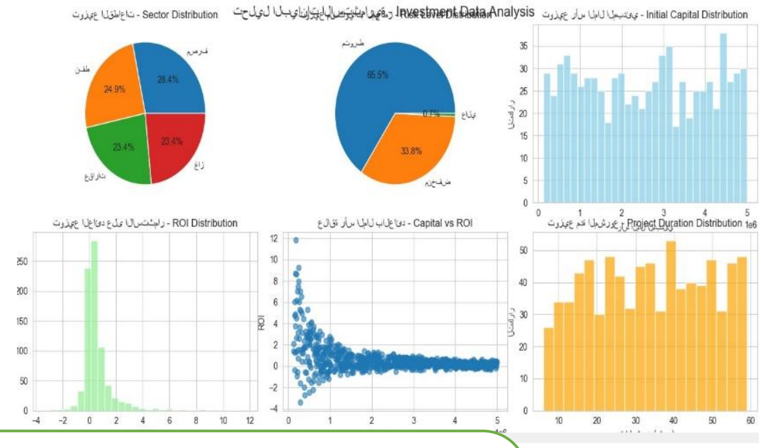
**The expected results from this experimental model is a comprehensive framework applicable across multiple sectors.**

**An improvement in prediction and classification accuracy by a significant margin**

**An increase in risk prediction capabilities, enhancing planning and crisis response.**

## Results

The image presents an analysis of investment data using various graphs that include sector distribution, initial capital, project duration, and return on investment (ROI).




We observe that the oil and gas sector dominates the distribution, while investment returns are volatile and tend to cluster around values close to zero. It also appears that there is a weak inverse relationship between capital and return, indicating that larger projects do not always yield higher profits.

An image showing the importance of variables in an investment rating model shows that the risk score is the most influential, followed by regulatory risk and market volatility

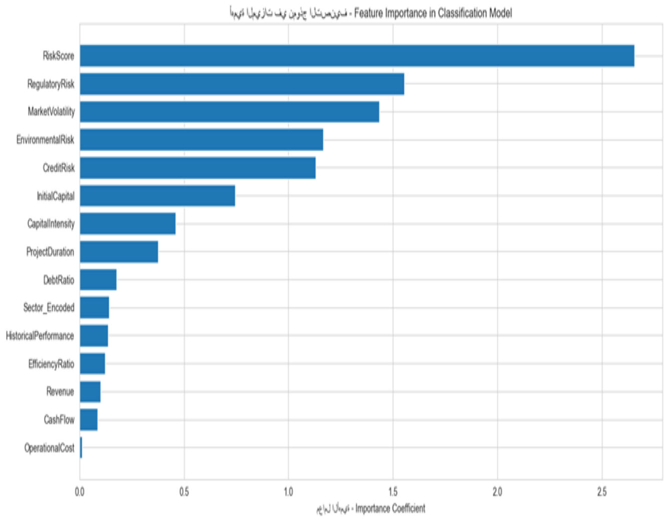
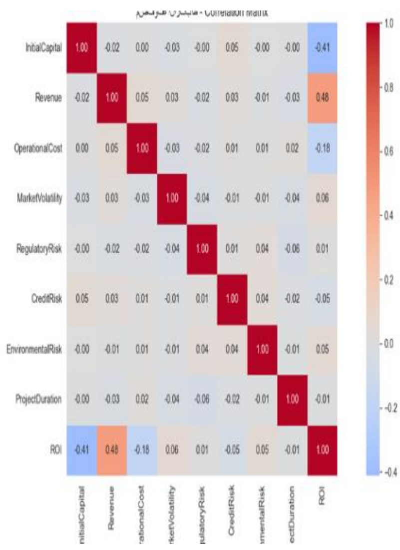



**Figure Resul 2**




The image displays the correlation matrix between investment variables.

We observe a strong positive correlation between revenue and ROI (0.48) and between capital and ROI (0.41).

In contrast, most regulatory and market risks exhibit a weak correlation with return on investment.

The financial variables such as revenues, cash flows, and operating costs had a weak impact compared to the risk factors. This indicates that the success of the investment decision depends more on the surrounding environment and risk management than on direct financial figures.

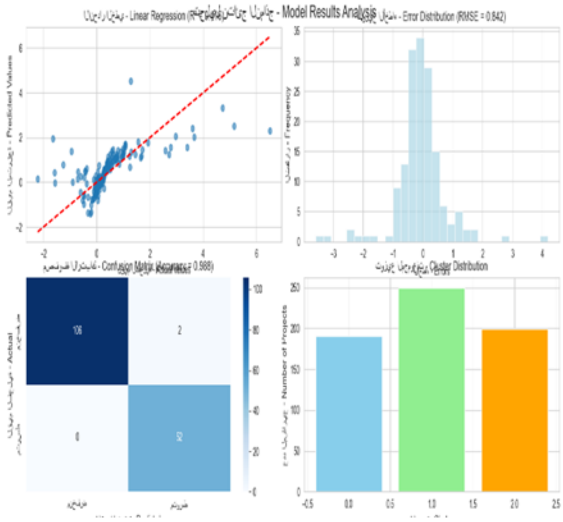
## Figure Result 3

The image represents a dashboard analyzing the results of a machine learning model. It includes:

A graph showing the relationship between predicted and actual values to measure model accuracy.

A chart showing the distribution of errors to determine how close they are to zero.

A confusion matrix showing the model's performance in classifying with high accuracy.




An image showing the summary results of a linear regression model , The model achieved high accuracy ($R^2 = 0.88$) with a medium error (RMSE = 0.842).

The confusion matrix demonstrates good discrimination between classes with an accuracy of approximately 0.988.

The error distribution is close to normal, reflecting the model's good fit to the data.

## Figure Result 4

An image illustrating the analysis of the distributions of characteristics in data using histograms.It shows that some variables are normally distributed, such as the risk index, while others are skewed or contain extreme values, such as efficiency and capital.

The goal is to understand the shape of the data before building models and improving their accuracy.

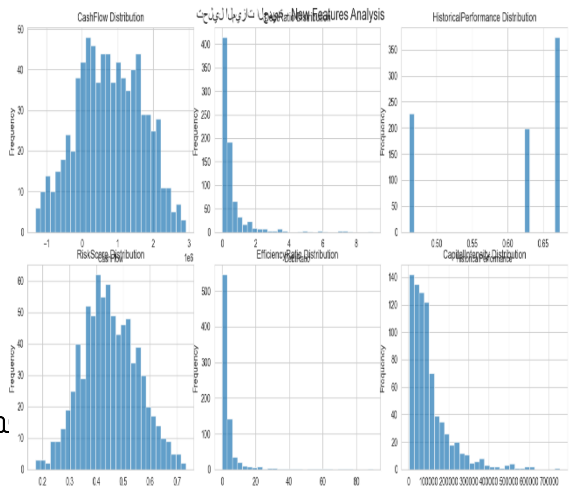


**Figure Result 5**

We observe that the oil and gas sector dominates the distribution, while investment returns are volatile and tend to cluster around values close to zero. It also appears that there is a weak inverse relationship between capital and return, indicating that larger projects do not always yield higher profits.

**Discussion)** – Summary Data from the Kaggle platform was used because it provides open and diverse datasets, especially in the areas of financial markets, economic indicators, and sentiment analysis. This data helped train machine learning models aimed at predicting crises and analyzing risks in investment sectors , Although some of the data suffers from updating or organization issues, Kaggle remains an effective platform for developing prototypes, especially given the limited access to real data in the financial field. Therefore, Kaggle data is considered a suitable starting point for investment crisis management applications using artificial intelligence.

## Conclusion

In conclusion, this applied research presents a flexible and customizable framework for crisis management across critical economic investment sectors based on the predictive capabilities of these methodologies in forecasting the realized fluctuations of financial and investment indicators, derived from our comprehensive dataset that spans from 2015 to 2022, with clear guidelines for application and evaluation, supported by a systematic analysis of bias and variance. This paper represents an important step through techniques in machine learning and forecasting fluctuations in financial markets and vital sectors like oil, gas, and real estate. By designing a model using neural network structures and hybrid models, the model is ready for practical application in financial institutions and can be continuously developed and improved based on new data and changing requirements in the oil and gas sector, opening the door to more advanced applications in the future.

An integrated model for financial crisis management was developed, demonstrating the model's capability to:

Accurately predict investment returns by reliably classifying financial risks

Identify similar investment groups and provide valuable insights for decision-making.

## Reference

1. Nguyen, Dat, et al. "Accurate Crisis-Related Data Classification on Social Networks Using Convolutional Neural Networks." Proceedings of the International Conference of the American Association for Artificial Intelligence on Internet and Social Media. Volume 11, Issue 1, 2017.

2. Ibrahim, Nehad M., et al, "Well performance classification and prediction: deep learning and machine learning long term regression experiments on oil, gas, and water production." Sensors 22.14 (2022): 5326.

3. Mora-Garcia, Raul-Tomas, Maria-Francisca Cespedes-Lopez, and V. Raul Perez-Sanchez. "Housing price prediction using machine learning algorithms in COVID-19 times." Land 11.11 (2022): 2100.

4. Kadkhoda, Saba Taheri, and Babak Amiri. "Hybrid Network Analysis and Machine Learning Model for Enhancing Financial Distress Prediction." IEEE Access 12 (2024): 52759-52777.

5.] Kumar, Satish, Amar Rao, and Monika Dutchak. "Hybrid Machine Learning Models for Predicting Volatility in Financial Risk Management." International Journal of Economics and Finance 98 (2025): 103915.

6.Shi, Xiangting , et al. "Deep Learning for Enhanced Risk Management: A New Approach to Financial Reporting Analysis." Journal of Computer Science 11 (2025): e2661.

7. Alhamid, Ahmad Abd, and Jiul Kim. "Machine Learning-Based Classification and Regression Approach for Sustainable Disaster Management: A Case Study of APR1400 in Korea." Sustainability Journal 13.17 (2021): 9712.

8. Nguyen, Dat, et al. "Accurate Crisis-Related Data Classification on Social Networks Using Convolutional Neural Networks." Proceedings of the International Conference of the American Association for Artificial Intelligence on Internet and Social Media. Volume 11, Issue 1, 2017.

9. Malampati, Morali. "Machine Learning and Generative Neural Networks in Adaptive Risk Management: Leading Secure Financial Frameworks." Kurdish Studies.

10 Ibrahim, Nehad M., et al, "Well performance classification and prediction: deep learning and machine learning long term regression experiments on oil, gas, and water production." Sensors 22.14 (2022): 5326.

11. Çılgın , Cihan, and Hadi Gökçen. "A hybrid machine learning model architecture with clustering analysis and stacking ensemble for real estate price prediction." Computational Economics 66.1 (2025): 127-178.

12. Jarašūnienė, Aldona, and Marius Gelžinis. "Risk and Crisis Management Strategies in the Logistics Sector: Theoretical Approaches and Practical Models." Future Transportation 5.2 (2025): 74.