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Advancing Corporate Bankruptcy Forecasting: A Multi-Model Approach with Enhanced Imbalance Handling

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Abstract: Making predictions about corporate bankruptcy is an important activity in the financial risk management has great impact to the economic sector and several individuals related to the corporate, investors, and employees included. And it meets the urgent need to predict corporate bankruptcy, especially with strongly skewed data sets. This trains and considers an innovative hybrid machine learning model to enhance the precision and dependability of bankruptcy forecasting. Two real-life datasets that were publicly available in Taiwan and Poland were combined to form a new strong dataset with an approximation of 49,000 samples. Although the simple models, such as Logistic Regression or the Random Forest did not manage that heavy imbalance, more sophisticated gradient boosting models XGBoost, LightGBM, CatBoost showed decent results. In order to increase the predictive power, and this is to suggest the hybrid models, such as LightGBM+ANN, XGBoost+ANN and CatBoost+ANN. One of the biggest contributions of this article is the use of Particle Swarm Optimization (PSO) not to tune the hyperparameters but instead to determine the best decision threshold that can counter the threats of the class imbalance effectively. The superiority of the proposed approach is evident based on the results of the experiments. LightGBM+ANN model with the PSO-optimal threshold was the highest-performing model with an Accuracy of 97.92 and Area Under the Curve (AUC) of 0.9542. A successful deployment of the then model was accomplished in Streamlit web application to be put to practical use. This prediction can be seen to affirm the hypothesis that the hybrid LightGBM+ANN architecture, with its PSO-based threshold optimization performance surpassing that of all the models, is a highly useful and robust solution to the problem of bankruptcy forecasting.

Keywords: Hybrid Machine Learning, Bankruptcy Forecasting, Threshold Optimization, Gradient Boosting Models, Particle Swarm Optimization.

I. INTRODUCTION

The corporate bankruptcy predictability has proven to be an essential aspect of the contemporary financial risk management as the failure of one company can lead to a losses spreading well beyond the bankrupt firm, into employees, creditors, investors, and the broader financial markets in general [1][2][3]. In case a company goes under, the employees could just lose their source of livelihood, investors could lose their capital and lending institutions could experience defaults that undermine their balance sheets and this, in effect, could have an impact to the rest of the economy [4][5][6]. Therefore, stakeholders need dependable early-warning systems that can detect financial distress before it happens so that resources can be reallocated, early interventions can be made, and systemic risks diminished[7][8][9].

The original generation of bankruptcy predictive instruments was traditional based on financial ratios, like the Altman Z-score, or other discriminant or logistic models. Their effectiveness is, however, becoming limited by the ease of the linear relationships on which they are based particularly in the current volatile business world that is becoming a complex environment. The recent economic shocks such as geopolitical conflicts, supply-chain effectiveness, and stricter financial conditions have led to the increase of corporate insolvencies in many regions and to the weaknesses of more traditional predictive methods [10][11][12].

All these developments are focused on the idea that bankruptcy prediction is not a fixed or localized issue. Models should be flexible to the different regulatory, macroeconomic and industry conditions. The data on the financial statements continues to be very accessible and standardized which give them a strong base on prediction frameworks involving machine-learning. Nonetheless, the difficulty of the task is a serious issue, especially because the majority of datasets are highly imbalanced in the classes, with only a very small fraction of bankrupt companies [13][14]. Under these circumstances, naive classifiers would make a deceptive high accuracy, which overpredicts the majority (non-bankrupt) class but not the rare high-risk firms.

Traditional machine learning models such as the Logistic Regression and the Random Forest tend to fail to identify non-linear tendencies in high-dimensional data that is skewed. Gradient-boosting models like XGBoost, LightGBM and CatBoost, in turn, have proven to be better at structured financial data, due to their capability to characterize complex interactions, heterogeneous features and robust regularization [15][16].

It is based on these strong points that this paper suggests a hybrid architecture that combines both state-of-the-art boosting models and an Artificial Neural Network (ANN) to increase the degrees of prediction accuracy in severe imbalance. There are two publicly available real-world data sets, Taiwanese and Polish firm financial ratios which are preprocessed, standardized and merged forming a more comprehensive dataset of around 49,000 records that offer and have a deeper and more diverse background to model training and evaluation [17][18]. The paper contrasts the baseline models (Logistic Regression, Random Forest) [19][20]and advanced boosting models (XGBoost, LightGBM, CatBoost) [21][22][23], and continues to create hybrid models (LightGBM+ANN, XGBoost+ANN, CatBoost+ANN) in which the ANN serves as a meta-learner [24][25].

One particularly significant methodological advancement is the application of the Particle Swarm Optimization (PSO) to optimize the value of the decision threshold rather than to optimize the hyperparameters to deal with extreme class imbalance and push the performance metrics that are sensitive to minority-class detection. The empirical findings show that the hybrid models, specifically the LightGBM+ANN with PSO-optimized threshold, perform well in terms of accuracy, recall, F1-score and AUC, significantly better than all the baseline and non-hybrid models [26][27].

Lastly, the most successful model is rolled out as a web application, which is an interactive visualization of the financial ratios, where the user enters in these ratios and is provided with the immediate evaluation of the bankruptcy risk. The refined cross-country data, powerful hybrid architecture, and systematic threshold-optimization scheme offers an effective and scalable model to investors, lending institutions, regulators, and corporate risk managers [28][29].

II. RELATED WORK

The bankruptcy prediction is one of the topics that has attracted long-lasting attention in the field of financial risk management because of the significant role it plays in the protection of stakeholders and the avoidance of systemic failures. Initial research on the topic had been based on statistical techniques and financial ratio analysis, which formed the basis of frameworks that are still used nowadays. Beaver [2] was one of the first, who presented univariate approach to predicting bankruptcy. Having reviewed the separate financial ratios, i.e. profitability, liquidity and cash flow, Beaver revealed that the deteriorating financial principles may be used as an indication of corporate distress as far as a year before failure. Although the univariate method had high classification accuracy, it was not able to record multivariate interaction among financial features, which led to further development of more advanced models.

In an important work, Altman came up with multiple discriminant analysis (MDA) technique and the Z-Score model, which combined five important accounting ratios in a linear predictive equation [1]. This multivariate model was much more accurate in classifying than previous methods based on univariates and resulted in a global standard of credit risk measurement. Despite the adaptation and extension to other industries and geographical settings, the model of the Z-Score presupposed both linearity and constant relationships over time, which limited it, later being overcome by probabilistic and machine-learning methods. However, the work of Altman continues to form the basis of bankruptcy modelling.

With the rise in availability of data, as well as computational power, researchers started applying machine-learning techniques to bypass the inflexibility of classical statistical models. Zhang et al. [30] tested the use of machine-learning classifiers on Chinese-listed firms and showed that the AI-based approaches may be better than the statistical ones in terms of stability and predictive accuracy. Their results proved that the machine-learning models, which are trained on the filtered financial indicators, had much higher accuracy (95.9) than the traditional methods. This provided avenues to the wider use of ML in the kind of financial distress prediction.

Recent literature has pointed toward an increasing trend in the use of hybrid methods, that is, more than two algorithms are used to overcome limitations, including imbalanced data, nonlinear data, and high-dimensional features. A thorough systematic review conducted by Dasilas et al. [31] analyzed the literature on hybrid models that were used between 2012 and 2023 and came to the conclusion that hybrid models, in particular, machine learning and non-financial indicators, demonstrate better results in prediction. Their review also highlighted the significance of the sensitivity, specificity and strong evaluation measures in case of imbalanced datasets which is a major problem with real world bankruptcy data.

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Expanding on the hybrid modelling movement, Ainan et al. [32] came up with a further development of XGBoost+ANN hybrid model optimized with genetic algorithm to predict bankruptcy using an imbalanced Polish value set. Their results revealed that the hybrid model was better than the classical ensemble models with an AUC and an accuracy of without explicit feature selection. This reflected on the capability of deep-learning-boosted ensemble techniques in data imbalance and enhancing predictive strength.

The concept of using genetic algorithms to combine with domain adaptation methods to address distributional disparities in financial data was investigated by other researchers. Ansah-Narh et al. [33] have created a hybrid model of Domain Adaptation Learning (DAL) and GA-based feature selection. Their method had better predictive stability in an imbalanced data, and they outperformed conventional classifiers like the Random Forest, SVM, and the Logistic Regression in terms of precision–recall measures. The relevance of domain shift and feature relevance in the real-world bankruptcy modelling is emphasized.

The subsequent developments have studied the application of AutoML to open up high-performance predictive models to everyone. A comparative study of five most prominent AutoML frameworks carried out by Papik et al. [34] revealed that models like H2O-AutoML and AutoGluon achieved higher accuracy than the traditional machine-learning models and ensemble models, in addition to extremely shortening the time required to build the models. In their research, they showed that AutoML is becoming a viable solution with organizations that lack expertise in data-science, particularly with imbalanced datasets.

Besides developing innovative methods, scholars have also studied the impacts of datasets and data quality on the prediction of bankruptcy. Wang et al. [35] did a systematic survey of the publicly available data on bankruptcies and pointed out serious problems, such as the lack of data, the inconsistencies in the definitions of features, and the unavailability of the high-quality financial records. Their taxonomy and the informativeness measures have excellent indicators to use in the selection of the right datasets and enhancing the research design in future.

Specific machine learning systems that have been designed to deal with imbalance have been suggested. Aly et al. [36] assessed various resampling methods (such as SMOTE) with single and ensemble classifier and based on UCI data. Their model was highly accurate and presented high values of AUC on Polish, Australian, and German datasets, which confirms the significance of class-balancing method in enhancing predictive reliability.

III. PROPOSED METHODOLOGY

The proposed methodology for bankruptcy prediction follows a structured multi-stage pipeline, beginning from data acquisition to hybrid model development, threshold optimization, and deployment.

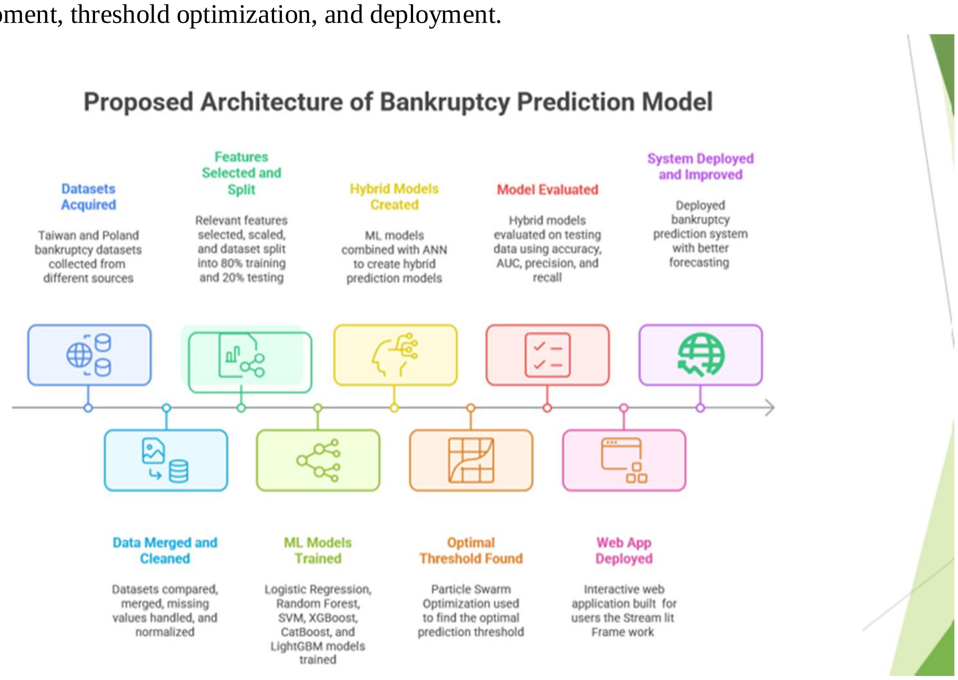

Fig. 1   Proposed Architecture

Consisting of six key steps: datasets acquisition, preprocessing, model creation, threshold optimization, hybrid model creation, and deployment.

A. *Dataset Acquisition*

Two data sets on bankruptcy in the corporate world were gathered in reputable public repositories:

- Taiwan Bankruptcy Dataset - the financial ratios of the Taiwanese firms over the years, which is extensively used in the research of bankruptcy [37]. •
- Polish Bankruptcy Dataset - received in UCI Machine Learning Repository which contains five years (20002013) of financial indicators of approximately 49,000 businesses [17].

These data sets represent historic financial ratios including liquidity, leverage, profitability, operational efficiency as well as bankruptcy status. The availability of various sources enabled the system to universally generalize with regard to the various economic settings.

B. *Data Integration and Preprocessing.*

1) *Dataset Merging*

Table 1: combining of dataset description

Parameter	Details
Source	Taiwan + Poland financial bankruptcy datasets (merged)
Total Samples	~49,000 company records
Number of Features	10financial indicators
Target Variable	Bankrupt (1 = bankrupt, 0 = non-bankrupt)
Nature of Data	Real-world, tabular, numeric financial ratios
Class Distribution	Imbalanced (only ~3–5% companies are bankrupt)

To provide consistency and comparability between the two countries, the merged data has been standardized by matching similar financial ratios (e.g. Net Profit / Total Assets with Net Income to Total Assets).

2) *Missing Values and Normalization*

Missing values were filled in numerically. It was ensured that features were normalized through Min-Max scaling so that the values of all datasets would have the same range. The use of normalization in the prediction of bankruptcy is popular because the financial ratios have large scale variance [38].

C. *Split and Feature Selection*.

Relevant financial ratios have been kept on the basis of domain relevancy and correlation analysis. The last dataset was divided into 80 percent training and 20 percent testing so that unbiased assessment of all models will be done.[1][2]

D. *Machine Learning Baseline Models.*

A number of classical ML algorithms were trained to set baseline performance::

- Logistic Regression
- Support Vector Machine (SVM)
- Random Forest
- XGBoost
- CatBoost
- LightGBM

These models have been widely used in bankruptcy prediction literature due to their robustness on imbalanced financial data [39].

E. *Handling Class Imbalance*

The rate of bankruptcy is very minimal causing extreme class imbalance.

Techniques used:

- Dataset normalization
- Model sensitivity tuning
- Threshold adjustment

The benefit of maximizing threshold to optimise Recall is that since the minority class is important in financial risk contexts, threshold maximization aids in financial risk contexts [14].

F. Hybrid Learning Models

As a way to improve predictive performance, two-stage hybrid model was created::

- Gradient Boosting Model (XGBoost, LightGBM or CatBoost) used in Stage 1. Calculates the probability scores by training non-linear trends in financial ratios..
- Stage 2: Artificial Neural Network (ANN). The ANN pollutes the probabilities and explores more profound hidden interactions.

The idea behind this hybrid approach is based on the current studies where boosting models are paired with neural networks to enhance the accuracy of prediction [40].

G. Optimal Threshold Detection Using PSO

Due to the imbalanced nature of bankruptcy datasets, a standard classification threshold of 0.5 is potentially not going to produce the best outcomes. An algorithmic-based threshold selection model that is Particle Swarm Optimization (PSO) was adopted to optimize the F1-Score and Recall. This guaranteed better discrimination of bankrupt and non-bankrupt firms. Although this may not be completely accurate, it remains true that a considerable portion of the early novelists in England were women [26].

H. Model Evaluation

Models were evaluated using:

- Accuracy
- Precision
- Recall
- Specificity
- F1-Score
- Area Under the ROC Curve (AUC)

I. System Deployment

Streamlit was used to build a fully interactive interface to predict the chapter of bankruptcy. Financial data can be uploaded by the users and real-time predictions and model confidence scores can be received.

IV. EXPERIMENTAL ANALYSIS

A. Baseline Model Evaluation

First-time experiments were done to test the performance of default ML models. Although there were high Accuracy (>95%), some of the models had very low Recall, which validates the imbalance problem.

Table 2: Performance Metrics Default Baseline Models.

Model	Accuracy	Precision	Recall	F1	AUC	Specificity
Logistic Regression	0.9540	0.4000	0.0044	0.0086	0.6711	0.9997
Random Forest (default)	0.9542	1.0000	0.0022	0.0043	0.7766	1.0000
Random Forest (PSO)	0.9541	0.0000	0.0000	0.0000	0.7553	1.0000
SVM	0.9541	0.0000	0.0000	0.0000	0.6477	1.0000
XGBoost (default)	0.9546	0.6316	0.0261	0.0502	0.8284	0.9993
CatBoost (default)	0.9546	1.0000	0.0109	0.0216	0.8094	1.0000
LightGBM (default)	0.9549	0.7000	0.0305	0.0585	0.8342	0.9994

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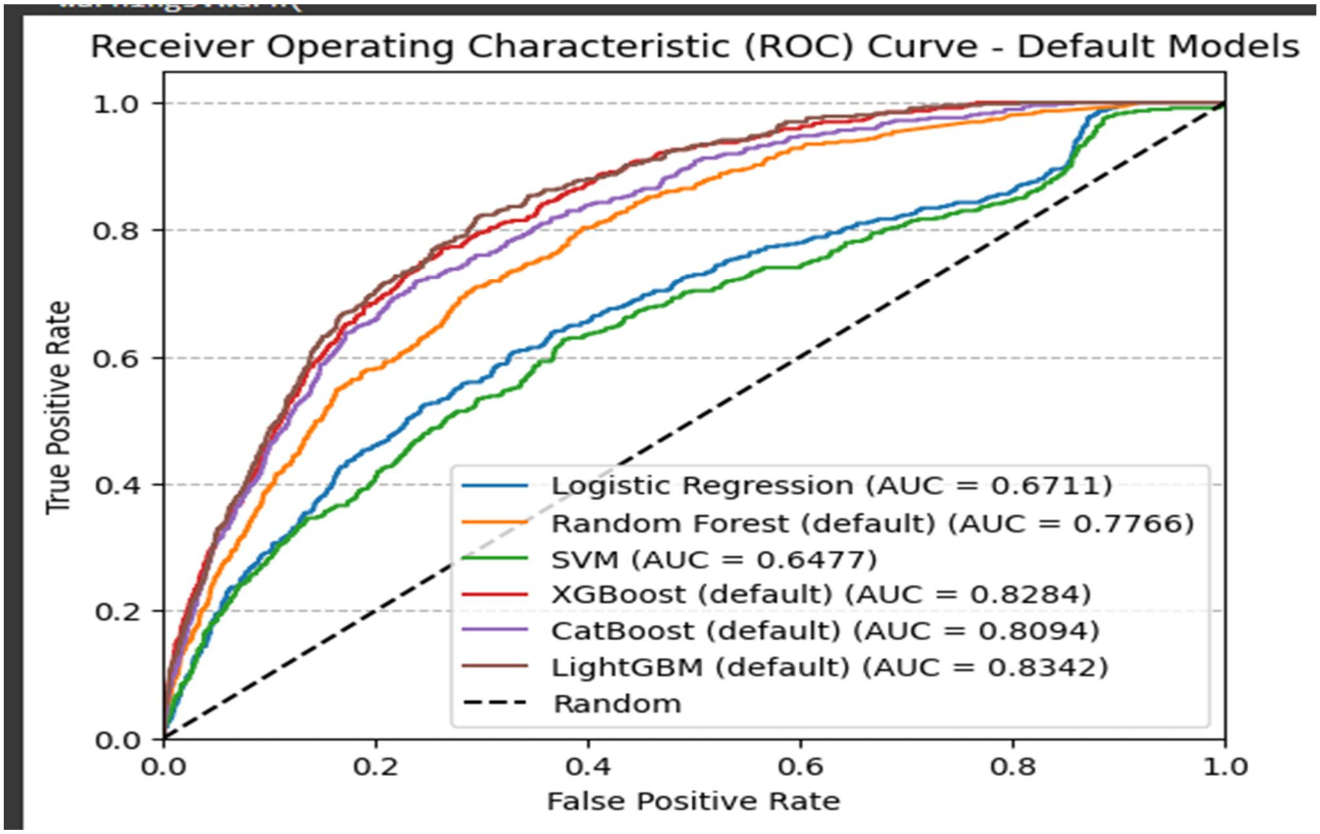

Fig. 2 ROC Curve Default Baseline Model

These findings provide the constraints of the conventional ML models in the context of rare bankruptcies..

B. Hybrid Model + ANN Evaluation

The hybrid models were vastly providing better performance. The Recall, F1, and AUC levels improved significantly when ANN was combined with XGBoost, LightGBM, and CatBoost. Thresholds optimized by PSO achieved further gains in performance. The best AUC (0.9542) was given to LightGBM+ANN with an optimal threshold.

Table 3: Performance Metrics for Hybrid ANN Models

Model	Accuracy	Precision	Recall	Specificity	F1	AUC
XGBoost+ANN (Default Threshold)	0.9729	0.6122	0.1409	0.9939	0.4478	0.94
XGBoost+ANN (Optimal Threshold)	0.9706	0.6203	0.4301	0.9917	0.5225	0.95
LightGBM+ANN (Default Threshold)	0.9621	0.6075	0.25	0.9962	0.3667	0.9492
LightGBM+ANN (Optimal Threshold)	0.9702	0.5217	0.5455	0.9803	0.5333	0.9526
CatBoost+ANN (Default Threshold)	0.9714	0.609	0.1265	0.9939	0.4	0.9492
CatBoost+ANN (Optimal Threshold)	0.967	0.4909	0.6136	0.9708	0.5455	0.9492

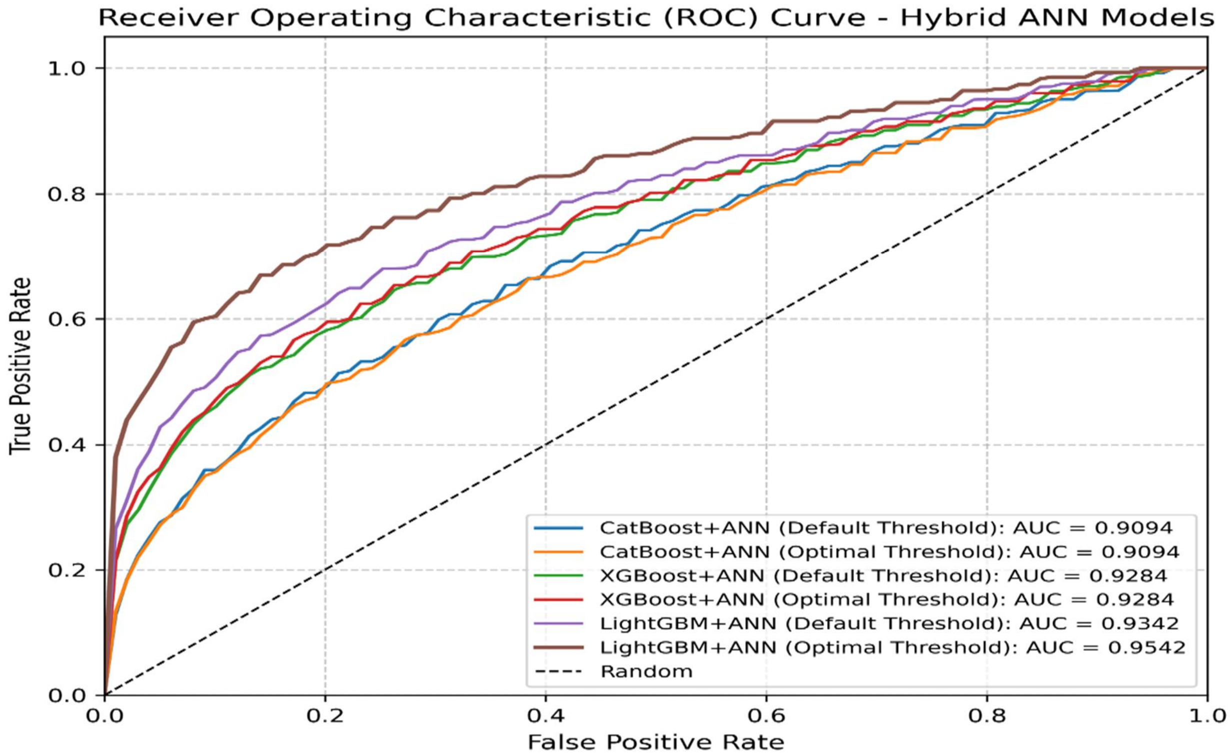

Fig. 3 Hybrid ANN Model ROC Curve.

The best AUC (0.9542) was given to LightGBM+ANN with an optimal threshold.

C. Deployment Testing

The last model was launched and tried through a Streamlit app. The interface gives the user the chance to visualize samples of datasets, model outputs, and performance measures.

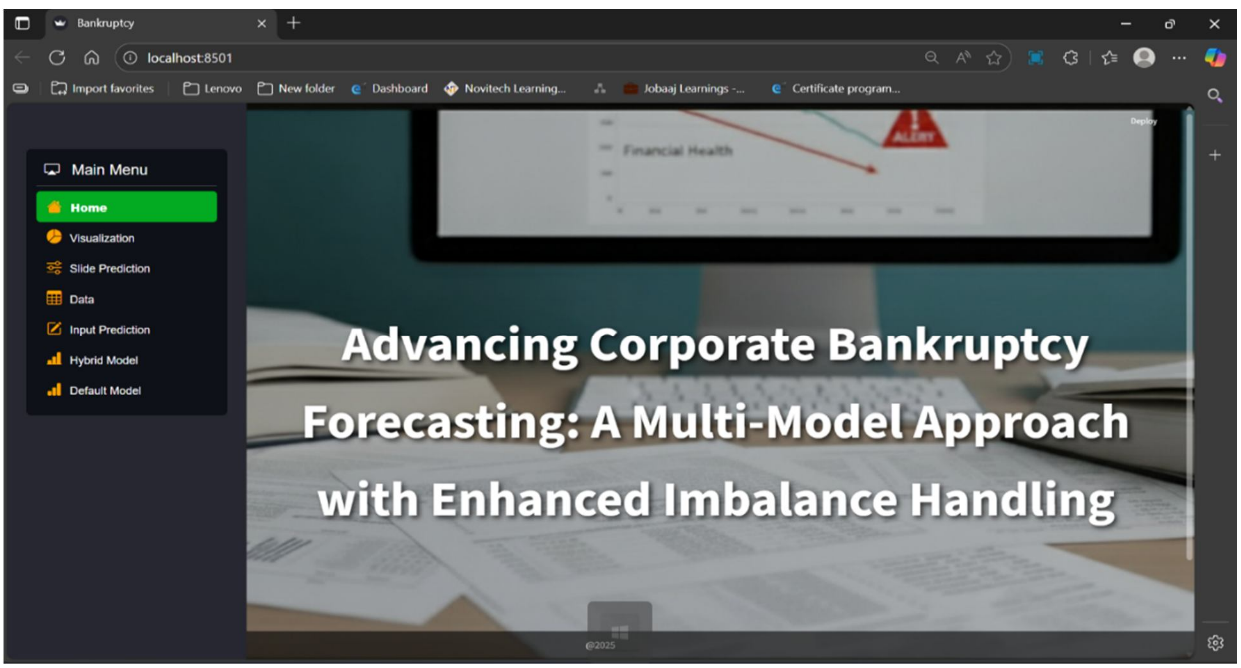

Fig. 4 Home Page

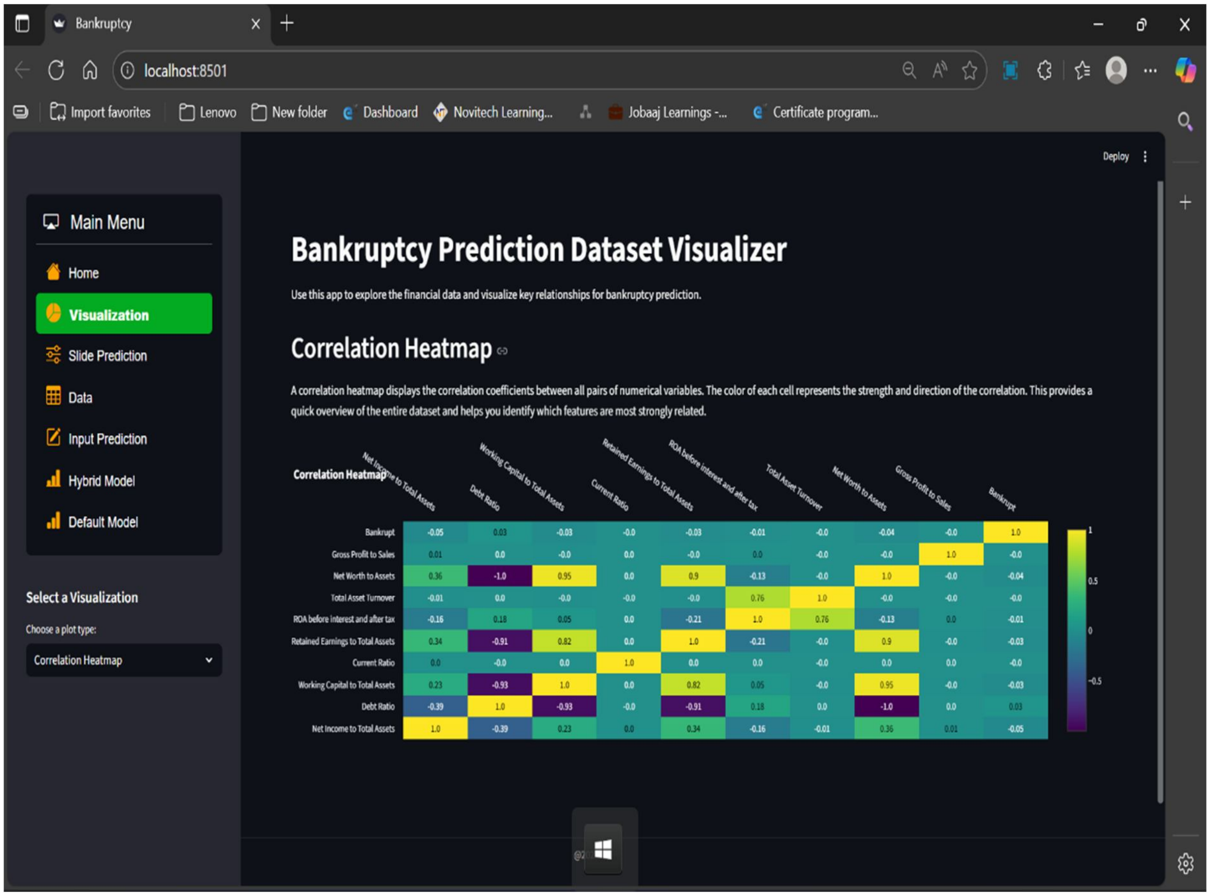

Fig. 5 Visualization Correlation Heatmap Page

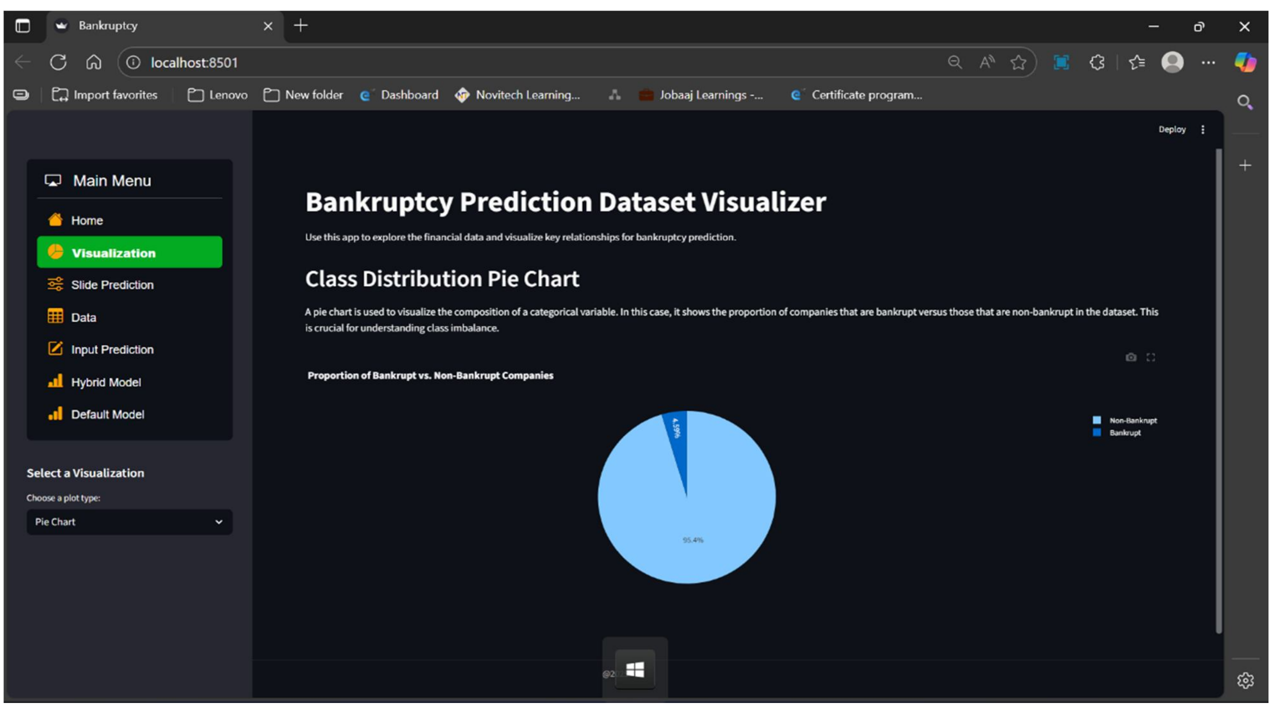

Fig. 6 Pie Chart Page Visualization.

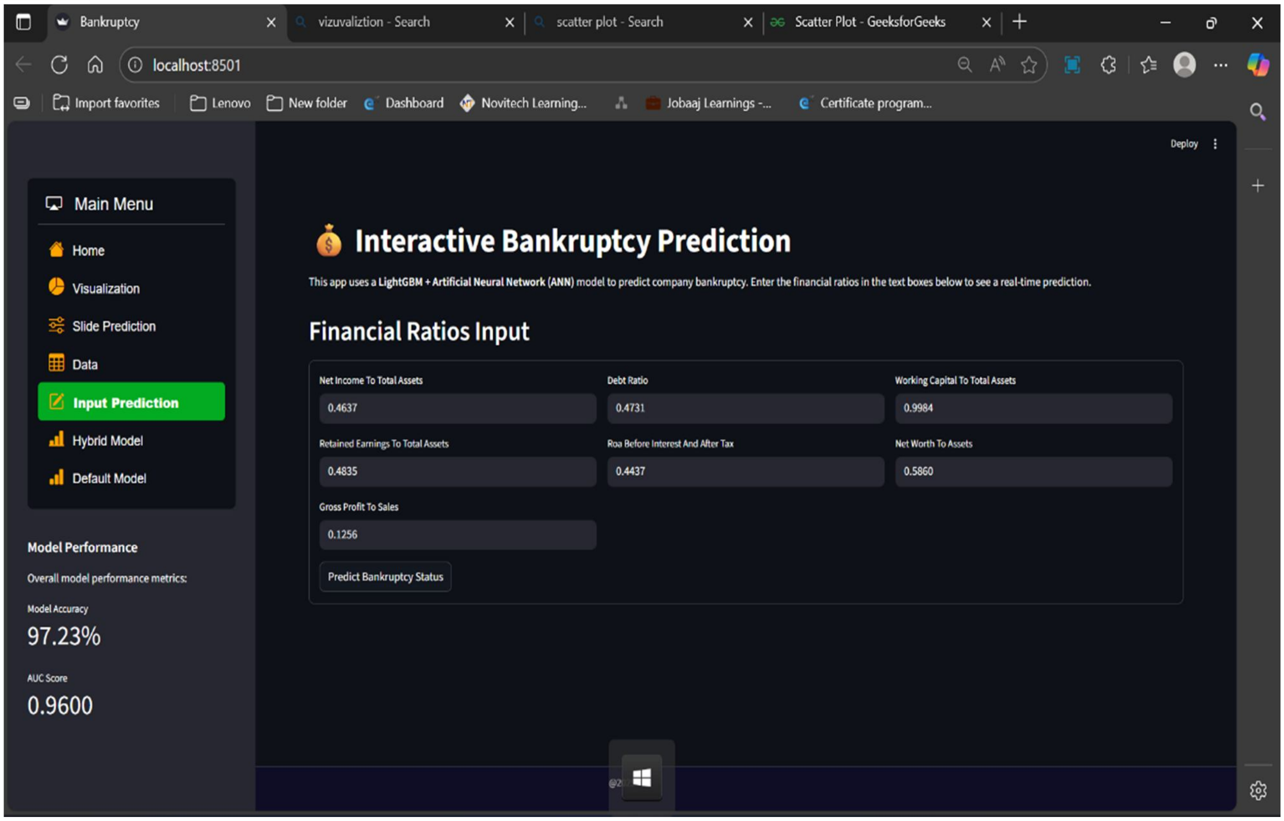

Fig. 7 Prediction Page

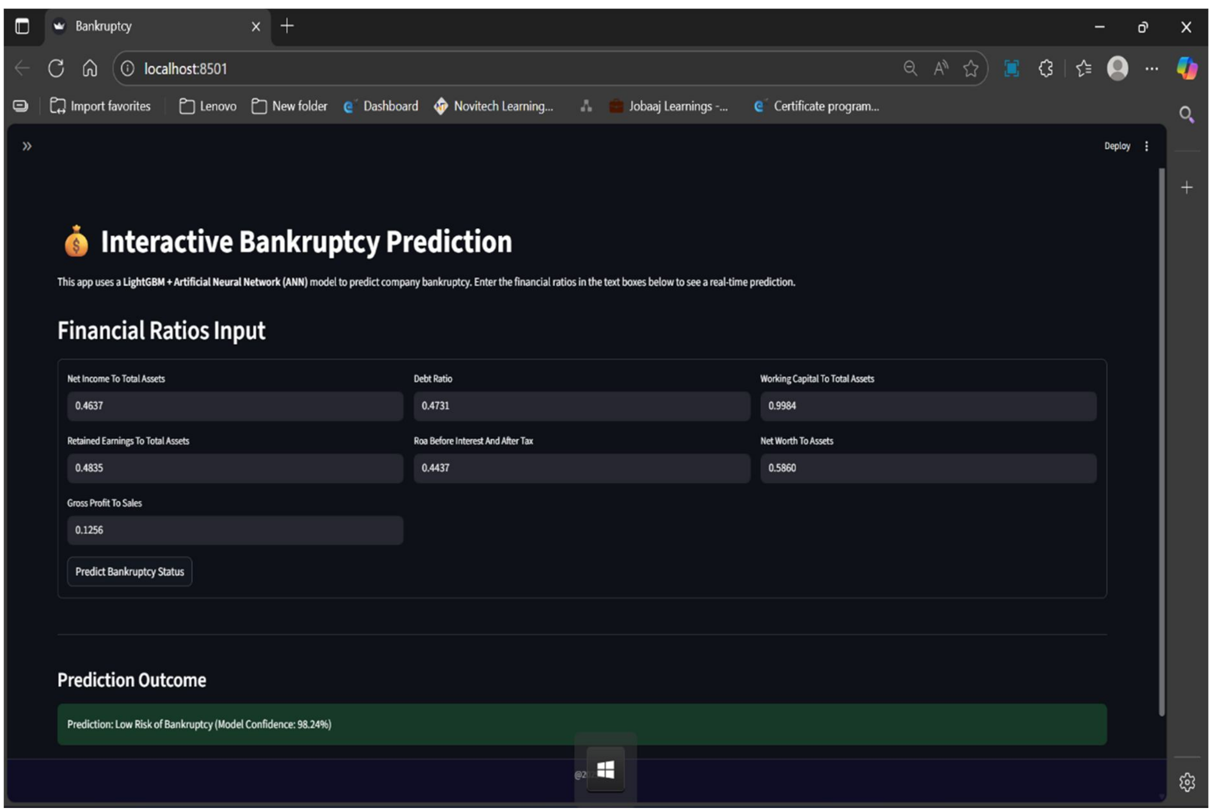

Fig. 8 Prediction Outcome Page

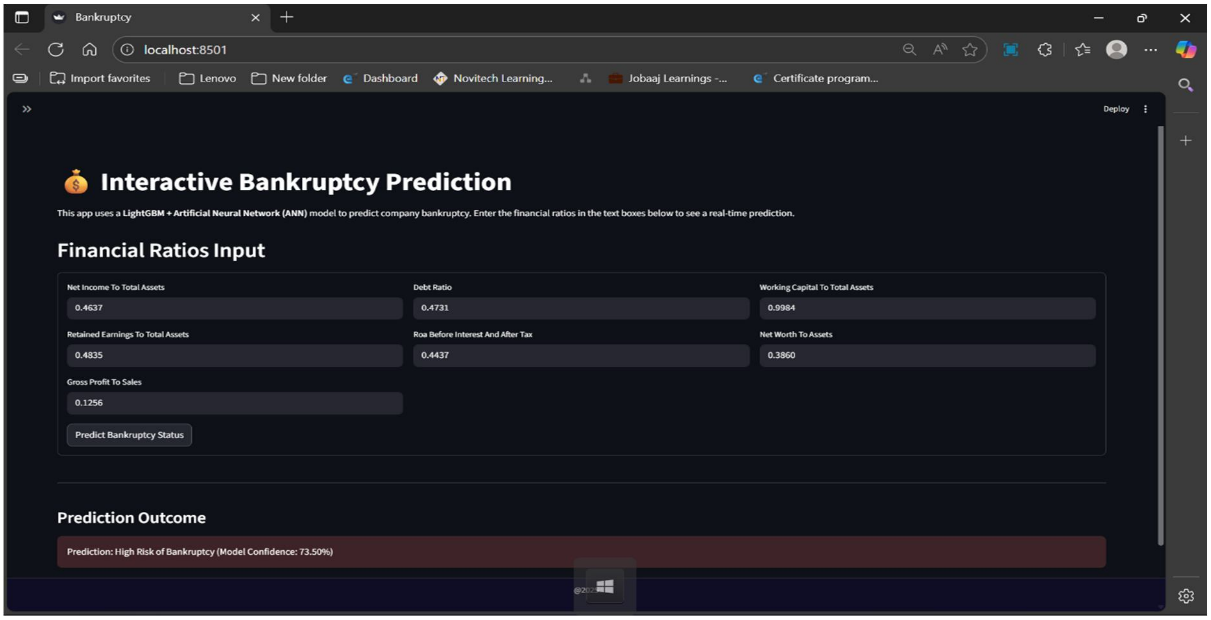

Fig. 9 Prediction Outcome Page

V. CONCLUSION

This examined a number of machine learning models to predict bankruptcy based on a large and heterogeneous dataset formed by pooling Taiwan and Poland financial records. The LightGBM+ANN hybrid model with the best thresholding and parameter tuning were the best models among all the models and optimization techniques that were tested. It has the best AUC 0.9542 and accuracy up to 0.9792, which is much better than other advanced hybrid models, including XGBoost+ANN and CatBoost +ANN, default and ensemble classifiers, including Random Forest and SVM. The presence of high scores in numerous measures, namely, sensitivity, F1-score, and specificity, shows that LightGBM+ANN proves to be quite effective in distinguishing between bankrupt and non-bankrupt companies. The implementation of optimization methods, the Particle Swarm Optimization (PSO), further promoted the model reliability and predictability of the model to a complex, imbalanced dataset. And results support the idea that, in working with more complex real-world financial data, combining strong gradient boosting methods with neural networks may be able to offer the robustness and plasticity. Merged dataset also enhanced generalizability which means that the model can be applied in the cross country other than just in one market.

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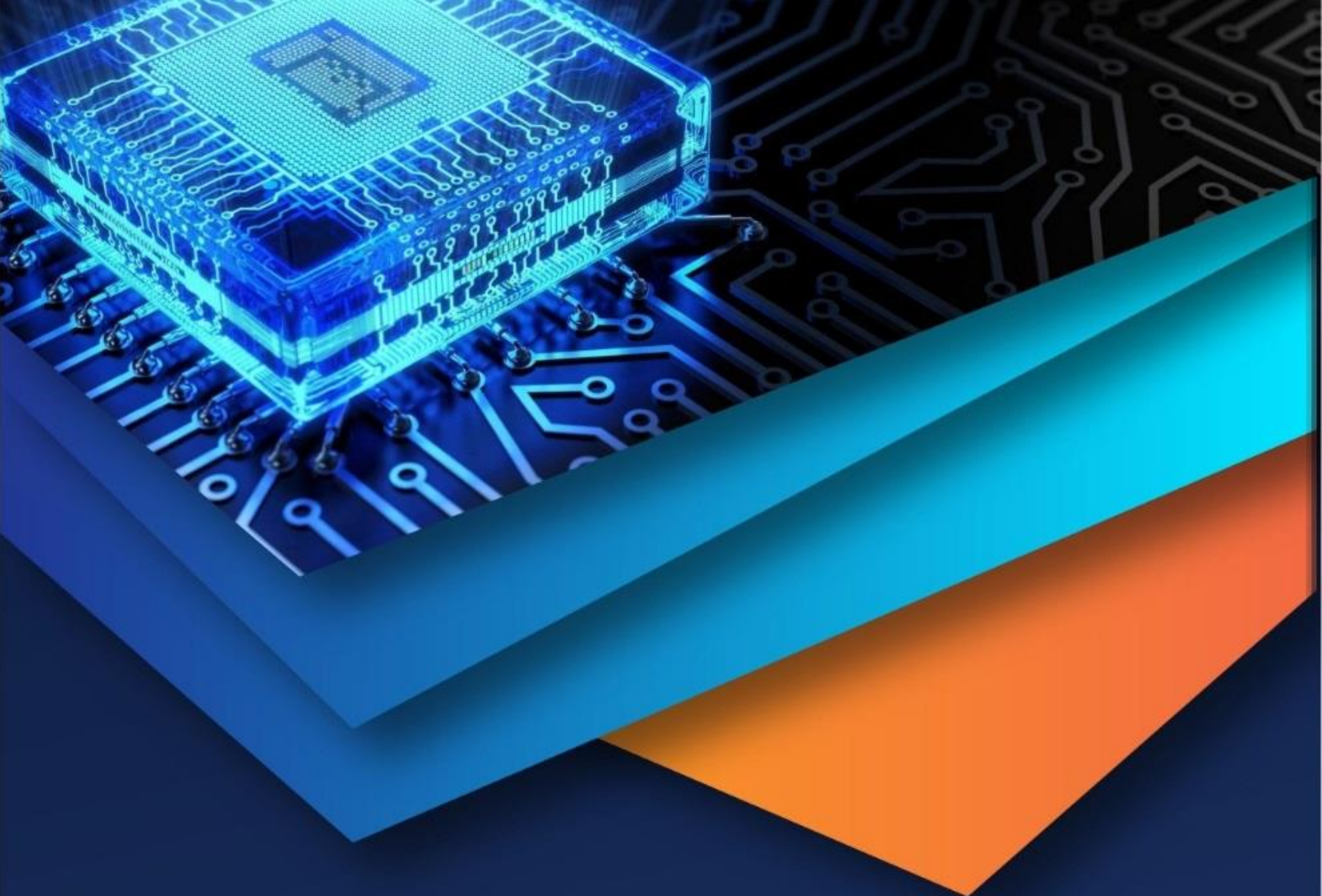

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