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The Study of the ANN Models for Predicting the Sovereign Bond Default Swaps

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Abstract-This study compares five Artificial Neural Network (ANN) models, such as Random Forests (RF), Support Vector Machine (SVM), Decision Tree, Naive Bayes Classifier (NBC), and K-Nearest Neighbor Algorithm (KNN), to predict the best model for sovereign bond default swaps (CDSs). We use the seven sentiment indicators, including the S&P500, VIX, USD index, LIBOR, Put/Call ratio, Commodity Research Bureau (CRB), and Association of Individual Investors (AAII). The result showed that the RF and Decision tree were the best prediction models for sovereign bond CDSs with higher accuracy and lower errors. These findings suggest that investors can use RF and Decision Tree models to set their future investment plans and minimize risk. Furthermore, they can use ANN models to forecast the CDS to build the hedging strategy when facing the downturn economic cycle.

Keywords: Sovereign Bond, Bond Default Swaps, Random Forest, Support Vector Machine, Decision Tree, Naive Bayes Classifier, K-Nearest Neighbor Algorithm

I. Introduction

When investors and securities issuers joined the securities market, they would suffer the risk that made them lose. As a result, the hedge investment strategy was very important to investors. The credit default swap (CDS) derivative could protect investors from credit default risk. [1] checked that CDS risk aversion could protect investors against high losses, but not all sectors were suitable for CDS risk aversion. CDSs were able to protect not only investors but also bond issuers. [2] showed that CDS trading could increase bond issuance, company valuation, trading, and holding liquidity to solve their financial problem. CDS trading could increase the leverage related to bankruptcy risk. [3] provided evidence of a liquidity spillover effect of CDS in the bond market. He found that CDS trading could enhance a company's bond issuance. When the company's rating was downgraded, CDS could protect the principle of investors and increase their willingness to hold more bonds.

Previous studies involved an artificial neural network (ANN). It was one of the best technologies for predicting the safety market through its high accuracy. [4] forecasted the closing price for the FinTech Exchange Traded Fund (ETF). The sentiment indicators included the volatility index (VIX) and the Put/Call ratio as inputs. ANN models with Random Forests (RF), Support Vector Machine (SVM), Naive Bayes Classifier (NBC), and K-Nearest Neighbor Algorithm (KNN). The results found that the best model was the SVM based on the Diebold Mariano test. [5] predicted share price index movement in Taiwan using the ANN, SVM, RF, and NBC models. They showed that RF was better than the other three forecasting models. [6] predicted the equity market and found that the decision tree model was slightly less predictable than the K-Fold model.

Sentiment indicators can affect ETFs, Exchange Traded Notes, and stocks. It represents a movement of investors, which can affect the prices of CDSs. This article picks seven entries: S&P 500, VIX, EURO/USD exchange rates, LIBOR, Put/Call ratio, Commodity Research Bureau (CRB), and Association of Individual Investors (AAII). The equity market can strongly reflect investor reaction if certain shock events or news have occurred. As the prediction tools, the ANN models can train the sentiment indicators and analyze the outcome for predicting the CDS. After reviewing previous studies, there needed to be more prediction of sovereign bond CDS. The motivation of this study is to use the sentiment indicators with ANN models to forecast and compare which model is best for sovereign CDS prediction. This article chooses the five ANN models such as Decision Tree, NBC, KNN, SVM, and RF because of a high accuracy prediction for securities in the empirical results.

This study aims to predict the sovereign bond CDS. Take into account the seven feelings of the investor indicators and measure their impact on the CDS. This research focused on ten countries' bond CDSs and used the ANN models for prediction. ANN models could accurately predict the CDS. The empirical result, which expects the best models, predicts sovereign CDSs and helps investors make future precision strategies.

The RF, SVM, and KNN models were the best that referenced previous studies. Although the decision tree and NBC models are not the perfect forecasting models in previous research, they still had greater accuracy in predicting safety. As a result, the decision tree and NBC models can be selected in this study and may differ from previous studies.

Previous research has used ANN models to predict equities, bonds, foreign exchange notes (ETN), exchange-traded funds (ETFs), etc. However, they did not study the domain of sovereign bond CDSs and compare the influence of the characteristics of sovereign bond CDSs. This article will start to fill the gap. The study has four goals:

- First, select the ten sovereign bond CDSs.
- Second, select seven sentiment indicators, measuring their impact on sovereign bond CDSs based on the RF model to rank the test size score from 0.1 to 0.3.
- Third, determine which of the five ANN models is most accurate for the price of sovereign bond CDSs using the average of the precision results.

II. Literature Review

CDSs could be used to hedge when investors have a higher default risk and a financial crisis. [1] discussed how CDSs could help reduce American equity risk. CDSs could be used to hedge when investors have a higher default risk and a financial crisis. The result confirmed that CDS could cover equity market risk when volatile stock prices. CDS risk aversion protected investors from high losses, but not all sectors were appropriate. CDS had a limited effect on protecting default risk, and investors could not expect to be fully protected against CDS during the financial crisis. The hedging strategy was critical in investment activities. When companies or countries were downgraded and bankrupted, CDS contracts could reduce investors' losses and increase their willingness to invest in higher-risk bonds.

CDS trading could boost a company's liquidity and improve its financial distress, but it could not fully protect investors. [2] examined the impact of CDSs on the company's liquidity management for the Over Counter (OTC) market. They found that if the credit quality of companies deteriorated, CDS transactions could add to the issue and trading of the company's bonds. The firm's cash flow would add to the risk of leverage and bankruptcy. Negotiating CDSs could increase the company's value and bring an advantage.

Investors purchased the bond to protect themselves from downgrading by companies or countries. The liquidity risk control was also an essential factor, [7] used the funding liquidity (shadow cost of capital for arbitrageurs) and asset-specific liquidity (determinants of margin requirements) to examine whether they were affected by the CDS prices and corporate bond spread basis. They found higher stock volatility and higher basis made by CDS, but the liquidity declined. Similarly, the liquidity of funds and special asset funds was related to high liquidity bonds, the basis of CDSs, and the liquidity risk to be reduced. These results proved that investors could only arbitrage if there were a high liquidity risk.

Others focused on issues related to sovereign bonds during the crisis. [8] used the [9] and [10] model (BSM model) and linear model to test the CDS spread for Spain, Ireland, Italy, and Portugal sovereign bonds risk from 2008 to 2012. He found a positive correlation between CDS spreads and the volatility index (VIX), MSCI, and S&P 500, excluding interest rate swaps. Sovereign bonds posed a high credit risk during the debt crisis, and the CDS was able to offer protection to issuers and investors. [11] analyzed the trading initiation of CDSs in the sovereign bond market using the logit and regression models. They used the MSCI equity index, the Global MSCI equity index, the level and slope of the yield curve, and the USD exchange rate to measure all the countries' sovereign bond spreads. Evidence shows that countries pose an increasing systematic risk, while the spread of CDSs could increase investor demand for hedging. CDS trading could reduce the default risk of sovereign bonds and make them easy to trade. For sovereign bonds, CDS was price effective and could improve the liquidity of sovereign bonds. Issuers had lower costs to borrow money and improve their debt distress.

[12] compared the market pricing of euro area government bonds and the corresponding CDSs of ten euro countries by utilizing the panel regression model with a countries-fixed effect and error correction model. They found that CDSs were strongly linked to sovereign bonds and that CDS premiums were more sensitive to financial conditions than bond spreads. The results showed that CDSs could reduce the credit risk of sovereign bonds and improve their liquidity.

CDS trade could have a significant impact on improving financial problems for businesses. [3] provided evidence of a liquidity spillover effect of CDS in bond markets. Empirical results have shown that CDS trading can enhance a company's liquidity and credit default risk. Investors began purchasing more CDS contracts to protect their principal against issuer default when the company's rating was lowered. CDSs have led investors to be willing to own more corporate bonds, reducing the cost of borrowing for businesses.

Predictive modeling was important when investing in an investment decision. Many previous studies investigating the selection of artificial neural network (ANN) models were more accurate than other prediction models. [30] tested the Black-Scholes-Merton model, which included cash prices, strike prices, interest rates, and European call and put option prices. AdaBoost, a Neural network autoregressive model with exogenous inputs (NNARX), SVM, and Fundamentals of Adaptive neuro-fuzzy inference system (ANFIS), were applied to predict the price of CDS contracts in North American and European countries. Among the models selected, the NNARX had the most predictive power and the least errors for predicting the price of CDS contracts.

Prior research has focused on predicting ETFs. [13] examined grey relational analysis (GRA) and artificial neural network (ANN) models, including Back Propagation Neural Network (BPN), Recurrent Neural Network (RNN), Radial Basis Function Neural Network (RBFN), Time-Delay Recurrent Neural Network (TDRNN) for the prediction of consumer ETFs. They used eight inputs: the put/call ratio, EUR/USD exchange rate, volatility index, Commodity Research Bureau (CRB) Index, New York Stock Exchange Composite Index, Arms index inflation, and interest rate. The grey relationship analysis compared ANN models to identify which model was the most appropriate for consumer ETFs. Using the criteria test, they demonstrated that BPN was the best model for predicting consumer ETFs. The results of the grey relationship test showed that the RBFN and TDRNN models were better than the BPN and RNN models. Test results indicated that BPN

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was the best model for forecasting consumer ETFs. [4] examined the hybrid forecasting model associated with the importance of Random Forest features in predicting the closing price of the FinTech ETF. They applied as inputs to EUR, VIX, Dow Jones Industrial Average and S&P 500, CRB Futures Price, and Put/Call ratio. The selected models included RF, SVM, NBC, KNN, Least Absolute Shrinkage, Selection Operator (LASSO), and Elastic Net and Theil-Sen regression to predict the end price for the FinTech ETF. The result found that the best hybrid model was the SVM based on the Diebold Mariano test.

To analyze stock price movement, [14] developed two efficient models related to comparing their performances in predicting the Istanbul Stock Exchange National 100 index daily movement. The result showed that three-layer forward ANN accuracy was better than an SVM model. [5] studied the stock price index in Taiwan. They applied a three-layered feed-forward ANN model, SVM, RF, and NBC. The outcome showed that RF was better than the other three prediction models. [15] predicted the Shanghai and Shenzhen stock market indices. They used independent variables to predict closing prices with SVM and KNN models. The result showed that both models were robust in predicting Shanghai and Shenzhen equity indexes. [16] used the ANN models to forecast the stock market price. They chose Random Forest and Gradient boost decision tree models to predict the stock market. The empirical result is that RF has the best foreseeable capability than Gradient boost decision trees. [6] designed the ANN models to help investors make decisions based on stock market forecasting. They used previous historical prices with K-Fold Cross Validation and Decision Tree models to predict stock prices on Amman Stock Exchange. The evidence revealed that there are better models for predicting the equity market than the decision tree model.

Previous studies looked at the relationship between the CDS market and securities. CDS could increase liquidity and credit risk for bonds and shares. It indicated that the investor was willing to hold more securities. In addition, issuers quickly received more financing to overcome the impact of the debt crisis because CDS could protect investors. However, previous research has rarely focused on predicting the price of CDS using ANN models, and these studies have focused solely on the expected price of CDS.

III. Data and Methodology

A. Data

This article collected weekly data sources from aaii.com, MarketWatch, and investment.com from 2018 to 2021, as shown in Table 1.

The website collected ten sovereign bond CDSs data and represented the global sovereign bond of CDS markets such as the USA, Australia, the United Kingdom, Italy, Russia, and Turkey based on ten years. In addition, France, Canada, Mexico, and Spain were given five years. Their durations were different because the recording data available were different. In addition, sovereign bond CDS were almost denominated in US dollars, except for the UK.

Table 1: The summary of sovereign bond CDS.

Country	CDS	Ticker	period
USA	US CDS 10 Years USD	USGV10YUSAB=R	2018.05.06-2021.12.26
Australia	Australia CDS 10 Years USD	AUGV10YUSAR=R	
UK	UK CDS 10 Years GBP	GBGV10YGBAB=R	
France	France CDS 5 Years USD	FRGV5YUSAC=R	
Canada	Canada CDS 5 Years USD	CAGV5YUSAC=R	
Mexico	Mexico CDS 5 Years USD	MXGV5YUSAC=R	
Spain	Spain CDS 5 Years USD	ESGV5YUSAC=R	
Italy	Italy CDS 10 Years USD	ITGV10YUSAC=R	
Russia	Russia CDS 10 Years USD	RUGV10YUSAC=R	
Turkey	Turkey CDS 10 Years USD	TRGV10YUSAC=R	

This article has introduced seven associated sentiment indicators that significantly impacted the securities market in previous studies.

(1) S&P500

The S&P 500 has been combined with 500 companies to their high trading prices on the U.S. stock market. This index was the stock market with all industries and a commentary index to measure the stock market. The S&P 500 Index could alter the price of CDS. [8] evidence found that CDS spreads positively correlated with S&P500. [17] showed that S&P500 could use to predict the exchange-traded note (ETN) with artificial neural network (ANN) models. These results showed that the S&P 500 index was the major variable used to measure securities and CDSs.

(2) The volatility index (VIX).

The VIX index, called panic indices, was the ticker for the Chicago Board Options Exchange Market Volatility Index. It measured the volatility of options of the Standard and Poor's 500 Index. So, VIX represented investor sentiment in the securities market. [8] showed that VIX could positively impact CDS prices and indicated that investor sentiment could affect their CDS trading activities. [4] used ANN models and saw that VIX could impact the ETF.

(3) Put/Call ratio

This variable could satisfy the views of investors in the market. If the Put /Call ratio is high, the investors are bearish on the stock market. Instead, investors have optimized the stock market while the Put/Call ratio has become lower. Thus, the Put / Call ratio was viewed as a sentiment indicator for investors. [13] reviewed the Grey Relational Analysis (GRA) and Artificial Neural Network (ANN) models for ETF prediction. They used the Put/Call ratio to examine the impact on the ETF. [4] predicted the ETF by ANN and found the Put/Call. The ratio could impact the ETF.

(4) Commodity Research Bureau (CRB)

The U.S. Commodity Research Bureau compiled the Commodity Research Bureau Price Index (CRB) was launched in 1957. It was covered by futures contracts such as energy, metals, agricultural products, livestock products, and soft products, and it was an important benchmark for movements in international commodity prices. The CRB is linked to the Fed's monetary policy and reflects inflation. The CRB represented economic expansion or contraction and could influence the stock market. [4] revealed that ROE might impact the price of ETFs. [17] showed that CRB could influence the ETN. It could affect commodity prices and the securities market.

(5) USD index futures

The USD index was derived from the average US dollar exchange rate relative to the six major international exchange rates. It showed the composite value of the dollar and measured the strength of various currencies. [17] demonstrated that the USD index could directly impact the ETN and that the change in the USD index could forecast the ETN by the ANN models. The other study, like [12], used the USD index to determine the CDS premium and sovereign bond spreads (Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain). They observed that the USD index could positively impact CDS premiums and sovereign spreads.

(6) LIBOR

The LIBOR (London Interbank Offered Rate) can measure the cost of bank-to-bank mutual lending and consists of quotes from several major banks. These banks forecast the interest rate of interbank loans daily, with maturities ranging from overnight to 12 months. When the LIBOR rate was raised, banks lent to interbank banks with a higher risk of default. [18] used the LIBOR rates to examine various maturities for Uncover Interest Rate Parity (UIP). They found that the LIBOR could positively affect the tenure of UIP. [19] examined that the policy reformed the LIBOR to change the arbitrage of investors and showed that changing the LIBOR could affect investors' arbitrage profit in the security market.

(7) Association of Individual Investors (AAII)

The AAII U.S. Retail Investor Sentiment Index was a survey conducted by the American Association of Individual Investors (AAII) and published the results every Thursday. [20] used the sentiment variables, including the AAII to predict the US stock market, such as Dow Jones Industrial Average, the Standard & Poor 500, the NASDAQ 100, and the Russell 3000 indices. They found that AAII had hurt the stock market. [21] used the sentiment variable (AAII) to measure the US equity market through an event study and multivariate regression. He found that AAII's sentiment could positively impact the stock exchange.

B. Model

(1) Random Forests (RF)

The ANN models are based upon [22]. In choosing the random forest model, [4] tested the hybrid prediction model and predicted the closing price of the FinTech ETF. They realized he could predict the ETF.

The Random Forest was introduced by [23] and combined with multiple Classification and Regression Trees, which were decision trees and calculated by the Gini algorithm. It ran the random distribution training data to improve the final operation result.

RF model was used in the Bernoulli experiment to divide and train data. It produced many decision trees and then split again into new nodes and grading until it was finished. Next, the majority voting system would pool the number of individual classifiers for analysis. It selected the output that obtained the most votes as the final decision [24]. It showed the RF training data and final predictive result.

Characteristics of the RF algorithm are used for every input into the algorithm and input data formation. The algorithm splits each sentiment variable to predict future outcomes for sovereign bond CDSs. Finally, arrange the ranking for each sentiment variable. The majority voting system collected and categorized the results and calculated the prediction score for

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the sentiment variables [31].

The function would be shown as follows:

$$(1) \quad B_j(x)) = \frac{P(c, B(x))}{\sum_{j=1}^{n} P(c, B_j(x))},$$

where $B_j(x)$ is the terminal node, x stands for a point connected with descending tree $T_j(j = 1,2, \dots, \mathrm{t})$, c represents the class $(c = 1,2, \dots, n)$, $\mathrm{P}(c|B_j(x))$ defined as the probability of tail at the terminal node x and c class.

(2) Support Vector Machine (SVM)

SVM was one of the best predictive models in prior research, and it belongs to a general feed-forward network [25]. [4] examined and compared the forecasting model to predict the closing price of the Financial Technology ETF. They found that the accuracy of SVM was better than the RF model in predicting the ETF.

SVM was a supervised machine learning to minimize errors and estimated a classified separating function (hyperplane). It also maximizes a specific value to make the best choice. The value was the minimum difference between the separating function and all training samples.

The assumption of the sample belonged to two classes and used this sample to train the SVM to obtain the maximum interval hyperplane. The sample points on the edges are called support vectors.

The separating function related to SVM was a linear combination of kernels related to support vector classification and support vectors.

This function could be described as:

$$\sum_{x_j \in S} f(x) = \sum v_j y_j K(x_j, x) + \theta, \qquad (2)$$

where $K(x_j, x)$ represents the kernel function, x_j stands for the training patterns, y_j define {+1,-1} following the class labels, v_j denotes the accordance with coefficient, θ is the offset, and S represents the set of support vectors.

(3) Decision tree

[6] used the K-Fold and Decision Tree model to predict the stock market. They evidenced that the Decision Tree model was not the best compared with K-Fold. [16] forecasted the stock market using the ANN models. They found that Gradient boost decision trees were not the best model to predict the stock market.

The Decision tree model split was introduced by [26], and it classified the observation data into one of two features' values and trained the data to generate the information gain. The larger the information gain, the higher the predictive ability.

Decision tree learning, as a common approach in data mining, trained the sample data and classified two feature outcomes that represented the information. The processing of the test generated many branches. The root node is split into many internal nodes and then divided into leaf nodes. The larger information gain represented that this model had high accuracy when combined with all leaf nodes.

In the learning process of the decision tree algorithm, the information gained was an essential indicator of feature selection. It was defined as a feature bringing how much information to the classification system. The more information it brought, the more critical the feature and the greater the corresponding information gain. The Decision tree model function was referred to [26] and described as:

$$I_G(D_p, f) = I(D_p) - \sum_{h=1}^{m} \frac{N_h}{N_p} \times I(D_h), (3)$$

where I_G is the information gain. f refers to the node used to split the feature. D_p represents as the data of the father node, D_h stands for data of the j child node, N_p is described as the father node's number of data, N_h is described as the h child node's number of data, and I defines as an impurity measure.

The function could be explained that the less the child node's sum of the impurity measure represented, the cleaner the model spilled. It indicated that the information gain increased and forecast accuracy raised.

The Gini impurity was a function that measured how well a decision tree was split. It helped this article to build a pure decision tree.

(4) Naive Bayes Classifier (NBC)

[4] used Naive Bayes to test the hybrid forecasting model to predict the closing price of the Financial Technology ETF. [5] predicted the stock price index movement. They evidenced that Naive Bayes was not the best prediction model for the stock price index.

The research on NBC was introduced by [28]. The NBC model assumed that all the random variables must be independent. Therefore, it could multiply the conditional probability to structure the joint probability distribution. NBC was combined with Bayesian networks and used the Kernel density function to estimate the best prediction levels. The Bayesian networks were also highly expandable. Therefore they needed many variables with parameters of linear to solve learning problems.

The Naive Bayes Classifier model was estimated by vector x= $(x_1, \dots, x_n)$ representing some n characters, and their probabilities could be described as:

$$P(C_z|x_{1,\dots,}x_n), \quad (4)$$

where each of z possible outcomes or classes are represented as C_z. The conditional probability of $P(C_z|x)$ could be shown as:

$$P(C_z|x) = \frac{P(C_z) \times P(x|C_z)}{P(z)}. \quad (5)$$

(5) K-Nearest Neighbor Algorithm (KNN)

[15] tested ANN model prediction for the Shanghai and Shenzhen stock market indices. They found that best forecasted the stock market indices were the KNN model.

The KNN algorithm was called the closest k-neighbor classification algorithm, created by [29]. It was used to classify the distances between all the sample data and uncertain values. According to Euclid's theorem, the principle of judgment was to identify which known (all the sample) and unknown characteristic values were closest to the unknown target feature value. Furthermore, the more numbers of characteristic values closest to the unknown target feature values, the higher the K value. It means the KNN had a more predictable ability. The KNN trained the data and calculated the distance between the observed and unknown values. After calculating all the value's distances, it found the nearest training values of level k distances and then classified the neighbors. The maximum number of frequencies was the examination value's forecast class in the KNN model.

The forecast function of KNN was shown as:

$$y = \frac{1}{k} \sum_{j=1}^{k} y_j \quad (6)$$

where y_j is the jth case of the sample and y stands for the forecast of the question point.

C. Test

The mean absolute error (MAE) was the loss function used for the regression model. It was the sum of the absolute values of the difference between the target and predicted values. It only measured the average modulus length of the error of the predicted value. The Mean squared error (MSE) was the most common regression loss function, and it was calculated by the sum of squares of the distance between the predicted value and the actual value. MSE could evaluate the degree of change in the data, and the smaller the value of the MSE, the better the accuracy of a predictive model. The Root Mean Square Error (RMSE) was the MSE function’s square root.

IV. Empirical Results

This study tested the ANN models, including Random Forest, Support Vector Machine, Decision tree, Naive Bayes, and K-Nearest Neighbor, to compare the best prediction model with the highest accuracy. However, the precision of ANN models was the random accuracy of random sampling.

This study used the seven inputs to measure how influential sovereign bond CDSs are. Each column represented each country's CDS, and each row represented the test size from 0.1 to 0.3. The size of the 0.1 test was represented by the ANN models sampled at random at 10% to predict sovereign bond CDS.

The results showed that the S&P500 indicator had the most significant effect on the US, the UK, Canada, Austria, France, Italy, Mexico, Spain, and Russia, with the highest feature importance score in the test size of 0.1. The feature that influenced Turkey significantly was the USD index in the test size of 0.1. In a test size of 0.2, the S&P 500 had the greatest impact on the USA, UK, Canada, Austria, Italy, Spain, and Turkey. The CRB achieved the greatest impact in France and Mexico. The USD index had the biggest impact on Russia. In a test size of 0.3, the S&P500 indicator had the most significant effect on the US, the UK, Canada, Austria, Mexico, and Spain. The results of the CRB had the greatest impact on France. The VIX has worked well in Turkey. The USD has been the strongest in Russia. Overall, the test sizes from 0.1 to 0.3 showed that the S&P500 indicator had the greatest effect on most countries' CDS, and the AAII had the slightest effect on each country's CDS, except for France, Turkey, and Russia.

Table 2 revealed the results of RF in predicting the sovereign bond CDS. RF accuracy at each test size was high overall. Consistent with [5], who demonstrated that the FR was the best model for the evolution of the stock market index. [16] demonstrated RF's most predictable ability to predict share prices.

In the test size of 0.1, the RF best predicted to Sovereign bond CDS of Canada with 99.10% accuracy and the lowest errors (MAE=0.0479, MSE=0.0126, and RMSE=0.1122). Furthermore, RF had the highest prediction of sovereign bond CDS of France, at 97.18% in a test size for 0.2, and sovereign bond CDS of Canada at 94.12% in a test size for 0.3. Overall, the RF model was the best prediction model for sovereign bond CDS of Canada, with the highest accuracy from test size from 0.1 to 0.3, and had the lowest errors, which measured MAE, MSE and RMSE less than 0.2. However, the FR had less precision than the United States and other countries because it had the weakest errors. The other finding was that Mexico, Spain, Italy, Russia, and Turkey had higher errors than the other five countries from test sizes from 0.1 to 0.3. It implied that RF could not predict these countries precisely, especially Russia, which had the highest errors based on MAE, MSE, and RMSE).

Table 3 shows the SVM model's results and its poor accuracy in predicting all sovereign bond CDSs. The finding showed that the SVM had the highest accuracy to sovereign bond CDS of the UK based on test size 0.1 with 76.60% (MAE=3.3969, MSE=20.3250, and RMSE=4.5083), test size 0.2 with 87.15% (MAE=2.0665, MSE=7.0929, and RMSE=2.6632), and test size 0.3 with 89.14% (MAE=2.0390, MSE=6.6225, and RMSE=2.5734). The SVM predicted that Mexico, Spain, Italy, Russia, and Turkey had the greatest errors than the other five countries, and their results were similar to the RF model.

[14] compared ANN and SVM to three layers for predicting stock price movement. All three layers forward better than SVM. [30] used SVM to predict CDS differences. These previous studies were consistent with the findings in this article that the SVM had low precision compared to sovereign bond CDS.

Table 4 shows the decision tree results for the prediction of sovereign bond CDS. In the test size of 0.1, the decision tree was most accurate for Canadian sovereign debt CDSs, with 100% associated with no errors. In a test size for 0.2, the best prediction accuracy for the sovereign bond CDS of France was 95.16% (MAE=0.8718, MSE=2.4615, and RMSE=1.5689), but its errors were not the lowest compared with Canada (MAE=0.1212, MSE=0.1212, and RMSE=0.3482). In a test size of 0.3, the model predicted that the sovereign UK had the highest accuracy with 93.12% (MAE=1.1321, MSE=4.0755, and RMSE=2.0188), but its errors were still higher than Canada (MAE=0.1020, MSE=0.1020, and RMSE=0.3194). These results implied that the decision tree was perfectly planned for sovereign bond CDSs from Canada, the UK, and France. The decision tree predicts that Mexico, Spain, Italy, Russia, and Turkey had the highest errors compared to the other five countries and that their results were similar to the RF and SVM models.

Overall, they were the most accurate for each country. However, the previous study's results were inconsistent with this article. [16] highlighted that gradient pulse decision trees were not a good model for forecasting market prices. [6] demonstrated that the decision tree model had poor precision in predicting the stock market.

The results of the Naive Bayes Classifier model can be found in Table 5. The finding is that the sovereign bond CDS of Canada's accuracy is 93.28% in the test size for 0.1, 88.89% in the test size for 0.2, and 88.85% in the test size for 0.3. It implied that Naive Bayes had predicted the highest and lowest errors in Canada's sovereign bond CDSs. The NBC model predicted that Mexico, Spain, Italy, Russia, and Turkey had larger errors than the other five countries, and their results were similar to those of the RF, SVM, and decision tree models.

Table 6 revealed the results of KNN. [4] used ANN models to predict the closing price of the FinTech ETF and showed that KNN was not the best predictive model. Instead, [15] used the KNN model to forecast Shanghai and Shenzhen stock indices and found that KNN was very predictable.

The finding that KNN forecasted sovereign bond CDS of France had the highest accuracy of 92.41% in a test size for 0.1. KNN predicted the highest accuracy of the sovereign bond CDS of Italy is 93.26% in a test size of 0.2, and the highest accuracy of the sovereign bond CDS of the UK is 92.22% in a test size of 0.3. The KNN model predicted that Mexico, Spain, Italy, Russia, and Turkey had higher errors than the other five countries. Their results were similar to the RF, SVM, decision tree, and NBC models.

Table 7 clarified this study's prediction of precision models at ten sovereign bond CDSs. This study used the arithmetic mean to calculate the accuracy of each model and quickly compare the predicted capacity of 5 models. The RF and decision tree were more accurate on average than the other three models. It implied that RF and decision tree models best predicted ten sovereign bond CDS. Other results showed five models of mean predictions for 10 CDS of sovereign bonds. Of these, five models were predicted in the U.K. (88.74%), Canada (76.59%), and Italy (75.45%). The five models were less precise than predicting Turkey (47.44%) and the U.S. (48.74%).

In summary, the empirical results of the five models in a test size are from 0.1 to 0.3. The RF model was the best predictor of sovereign bond CDS in Canada. The SVM model was the best predictive model for UK sovereign debt CDSs. The decision tree model was highly accurate for sovereign bond CDS in Canada, the United Kingdom, and France. The Naive Bayes model had the best prediction for Canadian sovereign bond CDSs. The KNN model provides high precision for CDS sovereign bonds from the United Kingdom, France, Canada, and Italy. The average accuracy of the ANN models demonstrated that RF and the decision tree were the best models for forecasting sovereign bond CDSs.

Conclusion

This research used five models, including the RF, the SVM, the Decision Tree, the NBC, and the KNN, and applied seven inputs to predict the ten sovereign bond CDSs. The average prediction of five models showed that RF and Decision Tree were the best models. The results of features evidenced that the S&P500 indicator had the greatest effect on most countries' CDS, and the AAII had the least effect on each country's CDS, except for France, Turkey, and Russia.

This study has provided the best models for managers of major financial institutions to help them make sound investment decisions accurately. It benefited them to plan investment policies and lower the risk from business activities in the long run. The study compared the results of ANN models that could be used to predict the CDS and the security market, such as stock, bond, index, ETF, futures, and alternative investment tools.

For investors, the results of this article could predict security prices and trends with variable forecast outcomes. These results helped them make decisions about buying and selling all the time. They may use these ANN models to adjust their portfolios to maximize profits and reduce the risk of price declines.

With macroeconomic views, ANN models could measure countries' economic situations, such as labor force participation rates, exchange rates, and sovereign bonds. We could refer to the predictive results to identify the countries' economic cycles and analyze their future impact. The contribution of this article could help investors achieve the hedging strategy, specifically using ANN models in the CDS market, and improve their risk management.

Table 2: The results of the RF model

RF model					
Bond CDS	Test size	Accuracy (%)	MAE	MSE	RMSE
US	0.1	73.39	0.2500	0.2500	0.5000
	0.2	78.62	0.6452	1.0333	1.0160
	0.3	81.90	0.9130	5.4783	2.340
Australia	0.1	77.19	1.6279	8.8343	2.9723
	0.2	85.40	1.4999	8.5521	2.9244
	0.3	91.33	1.1665	3.3201	1.8821
UK	0.1	92.23	1.6824	6.2159	2.4932
	0.2	92.44	1.3486	4.1717	2.0425
	0.3	93.32	1.4679	4.7464	2.1786
France	0.1	97.34	0.8982	1.9113	1.3825
	0.2	97.18	0.8076	1.4350	1.1979
	0.3	93.39	1.2827	3.7672	1.9410
Canada	0.1	99.10	0.0479	0.0126	0.1122
	0.2	95.57	0.1404	0.0645	0.4553
	0.3	94.12	0.1348	0.0770	0.2775
Mexico	0.1	94.63	6.3910	84.4571	9.1901
	0.2	92.33	7.5141	95.2532	9.7598
	0.3	93.15	6.3776	97.7773	9.8882
Spain	0.1	88.67	4.3772	56.6220	7.5428
	0.2	94.65	3.1936	22.7002	4.7645
	0.3	93.67	3.9550	37.8576	6.1528
Italy	0.1	96.05	9.2781	143.2934	11.9705
	0.2	95.46	8.0915	120.2418	10.9655
	0.3	93.42	8.9437	185.5404	13.6213
Russia	0.1	88.29	9.0321	152.4031	12.3452
	0.2	87.28	6.9373	87.3942	9.3485
	0.3	87.21	8.4870	133.5445	11.5561
Turkey	0.1	76.42	23.5312	1224.3548	34.9908
	0.2	83.62	24.1097	1236.1303	35.1586
	0.3	86.65	26.8963	1155.0245	33.9857

Table 3: the results of the SVM model.

SVM Model

Bond CDS	Test size	Accuracy (%)	MAE	MSE	RMSE
US	0.1	47.11	1.7207	3.8487	1.9618
	0.2	24.88	1.2839	5.4955	2.3442
	0.3	17.61	1.6796	3.8487	1.9618
Australia	0.1	7.94	4.5077	35.6513	5.9709
	0.2	68.93	3.5019	18.1927	4.2653
	0.3	71.33	2.6882	10.7248	3.2749
UK	0.1	74.60	3.3969	20.3250	4.5083
	0.2	87.15	2.0665	7.0929	2.6632
	0.3	89.14	2.0390	6.6225	2.5734
France	0.1	54.29	5.1917	32.7935	5.7266
	0.2	34.95	4.6610	33.0525	5.7491
	0.3	21.35	5.6879	44.8241	6.6951
Canada	0.1	39.34	0.8111	0.8522	0.9231
	0.2	7.36	0.7716	1.3491	1.1615
	0.3	7.64	0.9054	1.2102	1.1001
Mexico	0.1	17.92	28.5783	1291.9080	35.9431
	0.2	60.67	16.8314	488.5515	22.1032
	0.3	61.72	17.0948	546.5899	23.3793
Spain	0.1	58.11	11.3323	209.2719	14.4662
	0.2	56.53	10.3996	184.5169	13.5837
	0.3	56.66	12.3042	259.1521	16.0982
Italy	0.1	59.20	32.0712	1479.8722	38.4691
	0.2	16.39	40.4768	2213.6712	47.0497
	0.3	17.81	40.4330	2317.8144	48.1437
Russia	0.1	52.41	19.3954	619.2942	24.8856
	0.2	29.41	14.8732	484.8842	22.0201
	0.3	46.06	18.5662	563.1800	23.7314
Turkey	0.1	21.47	56.0613	4077.1546	63.8526
	0.2	16.34	64.9856	6313.1832	79.4556
	0.3	43.61	56.9980	4876.9045	69.8348

Table 4: The results of the Decision Tree model.

Decision tree model					
Bond CDS	Test size	Accuracy (%)	MAE	MSE	RMSE
US	0.1	96.56	0.2500	0.2500	0.5000
	0.2	85.89	0.6452	1.0326	1.0160
	0.3	26.95	0.9130	5.4783	2.3406
Australia	0.1	78.44	1.4500	8.3500	2.8896
	0.2	79.81	2.1282	11.8205	3.4381

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	0.3	84.33	1.6897	5.8621	2.4218
UK	0.1	94.86	1.2222	4.1111	2.0276
	0.2	86.06	1.6389	7.6944	2.7739
	0.3	93.32	1.1321	4.0755	2.0188
France	0.1	94.29	1.3000	4.1000	2.0248
	0.2	95.16	0.8718	2.4615	1.5689
	0.3	81.52	1.7069	10.5345	3.2457
Canada	0.1	100.00	0.0000	0.0000	0.0000
	0.2	91.68	0.1212	0.1212	0.3482
	0.3	92.21	0.1020	0.1020	0.3194
Mexico	0.1	89.58	8.6500	164.0500	12.8082
	0.2	93.67	6.5128	78.6154	8.8665
	0.3	88.37	8.7931	166.0345	12.8854
Spain	0.1	52.44	6.5000	237.6000	15.4143
	0.2	81.75	5.2564	77.4615	8.8012
	0.3	72.26	6.7241	6.15285	12.8787
Italy	0.1	93.38	11.0500	240.2500	15.5000
	0.2	86.70	13.0256	352.1538	18.7658
	0.3	83.27	13.7586	471.9310	21.7240
Russia	0.1	83.80	12.0500	210.8500	14.5207
	0.2	88.57	6.2821	78.5385	8.8622
	0.3	88.73	7.8448	117.6724	10.8477
Turkey	0.1	48.68	33.9000	2664.7000	51.6207
	0.2	73.85	28.9487	1973.3077	44.4220
	0.3	59.12	41.5345	3535.5345	59.4604

Table 5: The Naive Bayes Classifier (NBC) model.

Naive Bayes Model					
Bond CDS	Test size	Accuracy (%)	MAE	MSE	RMSE
US	0.1	54.04	1.2925	3.3447	1.8288
	0.2	27.93	1.6969	5.2723	2.2962
	0.3	14.67	1.6218	6.3987	2.5296
Australia	0.1	45.32	3.3792	21.1772	4.6019
	0.2	78.16	2.8073	12.7898	3.5763
	0.3	70.80	2.5401	10.9247	3.3052
UK	0.1	81.62	2.9892	14.7104	3.8354
	0.2	88.18	1.8674	6.5212	2.5537
	0.3	85.16	2.4142	9.0510	3.0085
France	0.1	58.44	4.4532	29.8192	5.4607
	0.2	46.46	4.3702	27.2036	5.2157
	0.3	43.15	4.5417	32.4024	5.6923

Canada	0.1	93.28	0.2496	0.0944	0.3072
	0.2	88.89	0.3359	0.1618	0.4023
	0.3	88.85	0.3085	0.1460	0.3822
Mexico	0.1	50.67	18.1129	776.3958	27.8639
	0.2	67.54	14.7428	403.1363	20.0783
	0.3	63.30	17.3135	523.9678	22.8903
Spain	0.1	77.57	8.0780	112.0764	10.5866
	0.2	64.81	9.6945	149.3595	12.2213
	0.3	57.43	11.9059	254.5720	15.9553
Italy	0.1	67.12	27.9877	1192.6812	34.5352
	0.2	80.05	17.4007	528.3135	22.9851
	0.3	68.85	21.2716	878.5648	29.6406
Russia	0.1	66.79	14.2605	432.2062	20.7896
	0.2	49.60	12.8921	346.2009	18.6065
	0.3	46.78	17.1562	555.6440	23.5721
Turkey	0.1	18.71	56.6692	4220.8471	64.9680
	0.2	30.73	57.9771	5226.9337	72.2975
	0.3	42.77	57.6671	4949.9481	70.3559

Table 6: The results of the KNN model.

KNN Model					
Bond CDS	Test size	Accuracy (%)	MAE	MSE	RMSE
US	0.1	45.62	0.8875	3.9575	1.9893
	0.2	24.88	1.2839	5.4955	2.3442
	0.3	31.03	1.2807	5.7217	2.7424
Australia	0.1	74.35	2.0700	9.9340	3.1518
	0.2	76.04	1.9333	14.0318	3.7459
	0.3	87.45	1.4586	4.6945	2.1667
UK	0.1	91.52	1.9778	6.7867	2.6051
	0.2	89.22	1.6889	5.9511	2.4395
	0.3	92.22	1.4679	4.7464	2.1786
France	0.1	92.41	1.7120	5.4440	2.3332
	0.2	87.56	1.7641	6.3200	2.5140
	0.3	78.74	2.3414	12.1166	3.4809
Canada	0.1	90.29	0.2118	0.1365	0.3694
	0.2	85.77	0.2606	0.2073	0.4553
	0.3	74.77	0.3469	0.3306	0.5750
Mexico	0.1	61.39	14.0100	607.6900	24.6514
	0.2	60.67	16.8314	488.5515	22.1032
	0.3	57.57	13.1828	605.8159	24.6133
	0.1	78.14	6.5200	109.2080	10.4503

Spain	0.2	78.56	6.2513	91.0021	9.5395
	0.3	60.30	8.8138	237.3793	15.4071
	0.1	90.59	14.4100	341.4740	18.4790
Italy	0.2	93.26	9.6513	178.3610	13.3552
	0.3	90.18	11.4621	277.0262	16.6441
	0.1	63.22	13.6800	478.6760	21.8787
Russia	0.2	75.52	10.2359	168.1600	12.9677
	0.3	75.01	12.0310	260.9731	16.1547
	0.1	37.91	42.7700	3223.9020	56.7794
Turkey	0.2	47.94	47.7180	3928.1282	62.6748
	0.3	23.84	60.9759	6586.8117	81.1592

Table 7: The average precision of ANN models. Unit: %

Bond CDS	RF	SVM	Decision tree	NBC	KNN	Average accuracy
US	77.97	29.87	69.80	32.21	33.84	48.74
Australia	84.64	49.40	80.86	64.76	79.28	71.79
UK	92.66	83.63	91.41	84.99	90.99	88.74
France	95.97	36.86	90.32	49.35	86.24	71.75
Canada	96.26	18.11	94.63	90.34	83.61	76.59
Mexico	93.37	46.77	90.54	60.50	59.88	70.21
Spain	92.33	57.10	68.82	66.60	72.33	71.44
Italy	94.98	31.13	87.78	72.01	91.34	75.45
Russia	87.59	42.63	87.03	54.39	71.25	68.58
Turkey	82.23	27.14	60.55	30.74	36.56	47.44

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