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BANKRUPTCY RISK FORECASTUSING DEEP LEARNING

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Abstract: Bankruptcy risk forecasting has long been a significant issue in finance and management science, which attracts the attention of researchers and practitioners. With the great development of modern information technology, it has evolved into using machine learning or deep learning algorithms to do the prediction, from the initial analysis of financial statements in the balance sheet data. This study introduces deep learning models for bankruptcy forecasting using company balance sheet. Although data are common, it is rarely considered in the financial decision support models. Deep learning has emerged and gradually developed into a powerful technique for a wide range of applications. We have used the deep learning models in bankruptcy prediction, including the classical deep learning methods such as Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN)

INTRODUCTION: Bankruptcy is a significant financial risk for any company, which can result in severe consequences for shareholders, creditors, and the economy as a whole. Therefore, predicting bankruptcy risk is crucial for both investors and policymakers. One of the ways to predict bankruptcy risk is by analyzing the company's financial statements, particularly the balance sheet data.We have used the deep learning models in bankruptcy prediction, including the classical deep learning methods such as Deep Belief Network (DBN) and Convolutional Neural Network (CNN). The model should also consider the industry in which the company operates and compare its performance with other companies in the same sector. This will help to identify industry-specific risks that could affect the financial health of the company. Additionally, the model should be able to capture the impact of macroeconomic factors such as interest rates, inflation, and GDP growth on the company's financial health and bankruptcy risk

we aim to overcome the limitations of traditional methods and provide a robust and efficient solution for bankruptcy prediction

The significance of this research lies in its potential to revolutionize the balance sheet. By automating the classification the proposed method can reduce manual labour, improve efficiency, and enhance quality control measures. Moreover, accurate bankruptcy prediction can facilitate better inventory management, packaging optimization, and meet specific market demands.

We will provide insights into the training process, model architecture, and the evaluation metrics used to assess the accuracy of our predictions.

Additionally, we will present experimental results demonstrating the performance and effectiveness of our proposed method, comparing it with existing approaches and highlighting its advantages.

METHODOLOGY:

Data Collection: Gather relevant financial data for a set of companies. This data typically includes financial statements such as balance sheets, income statements, cash flow statements, and other relevant financial ratios. You may also consider including non-financial data such as industry-specific information or macroeconomic indicator

Data Preprocessing: Clean the data and prepare it for analysis. This involves tasks like handling missing values, normalizing or standardizing the data, and encoding categorical variables if necessary. Ensure the data is in a format suitable for deep learning models.

Feature Selection/Engineering: Identify the most relevant features that can impact bankruptcy risk prediction. You can perform statistical analyses or use domain knowledge to select the most informative features. Additionally, you can engineer new features by combining or transforming existing variables.

Train-Test Split: Divide the dataset into training and testing sets. The training set is used to train the deep learning model, while the testing set is used to evaluate its performance. You can also use techniques like cross-validation or time-series splits depending on the nature of the data.

Model Selection: Choose a deep learning architecture suitable for bankruptcy risk prediction. Popular choices include feedforward neural networks, recurrent neural networks (RNNs), or convolutional neural networks (CNNs). Consider factors like model complexity, interpretability, and computational resources when selecting the model.

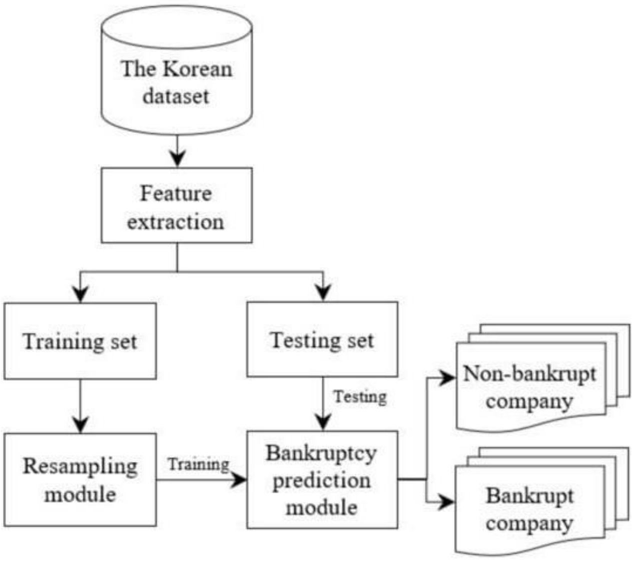
Model Training: Train the selected deep learning model using the training data. During training, the model learns to map the input features to the bankruptcy risk output. This involves adjusting the model's parameters through optimization algorithms like gradient descent to minimize a specified loss function.

Model Evaluation: Evaluate the trained model's performance using the testing data. Common evaluation metrics for bankruptcy risk prediction include accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curve analysis. Assess how well the model is able to distinguish between bankrupt and non-bankrupt companies.

Model Tuning: Fine-tune the model to improve its performance. This can involve adjusting hyperparameters, modifying the architecture, or applying regularization techniques to prevent overfitting. Iterate this step until you are satisfied with the model's performance.

Validation and Interpretation: Validate the model on new, unseen data to assess its generalization ability. Additionally, explore the model's learned representations and examine feature importance to gain insights into the factors contributing to bankruptcy risk.

Deployment and Monitoring: Once you have a satisfactory model, deploy it to make predictions on new data. Monitor the model's performance over time and update it as necessary to adapt to changing conditions or incorporate new data.



MATHEMATICAL MODEL:

Convolution:

The convolution operation in CNNs is used to extract features from input images. Given an input image and a set of learnable filters (kernels), the convolution operation is defined as follows:

Output feature map (activation map) at position (i, j) = sum of element-wise multiplication between the filter and the input image patch centered at position (i, j).

This can be expressed mathematically as:

$$H(i\,,j)=\sum m \sum n\ I(i+m\,,j+n).k(m\,,n)$$

where H(i, j) is the value in the output feature map at position (i, j), I(i+m, j+n) represents the pixel value in the input image at position (i+m, j+n), and K(m, n) represents the corresponding filter coefficient at position (m, n).

Pooling:

Pooling operations, such as max pooling or average pooling, are used to down sample the feature maps and reduce the spatial dimensionality. The pooling operation computes a single output value for a region of the input feature map. The mathematical formulas for max pooling and average pooling are as follows:

$$H(i\,,j)=\max m \max n\ F(i+m\,,j+n)$$

Max pooling:

$$H(i\,,j)=\max m \max n\ F(i+m\,,j+n)$$

Average pooling:

$$H(i\,,j)=1/m\text{-}n \sum m \sum n\ F(i+m\,,j+n)$$

Activation functions:

Activation functions introduce non-linearity into the CNN model and help in capturing complex patterns. Some commonly used activation functions in CNNs include ReLU (Rectified Linear Unit), sigmoid, and tanh. The mathematical formulas for these activation functions are:

Rectified Linear Unit (ReLU): ReLU is the most popular activation function in CNNs. It sets all negative values to zero and keeps positive values unchanged. The ReLU activation function is defined as f(x) = max(0, x). It helps in addressing the vanishing gradient problem and speeds up convergence.

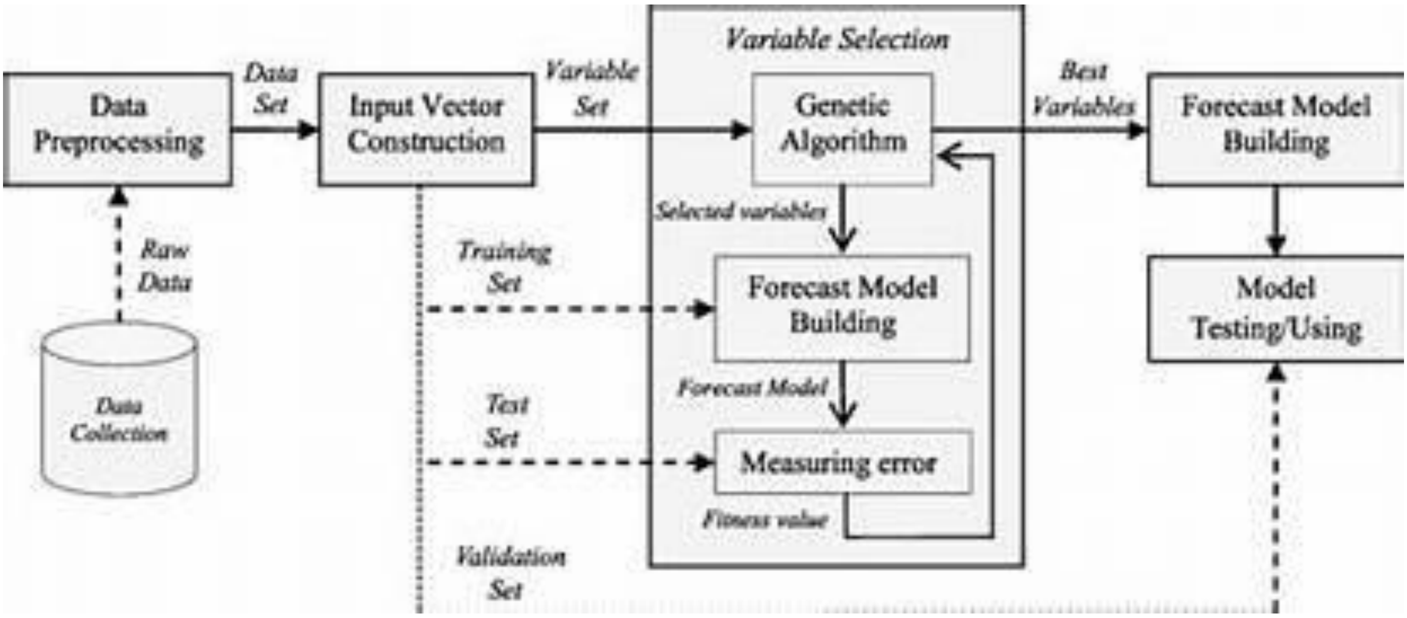
Sigmoid: The sigmoid activation function squashes the input values between 0 and 1. It is defined as f(x) = 1 / (1 + exp(-x)). Sigmoid is useful in models where we want to interpret the output as probabilities.

Hyperbolic Tangent (Tanh): Tanh is similar to the sigmoid function but squashes the input values between -1 and 1. It is defined as f(x) = (exp(x) - exp(-x)) / (exp(x) + exp(-x)). Tanh is centered at 0 and is sometimes preferred over sigmoid as it provides stronger gradients.

Softmax: Softmax is commonly used as the activation function in the output layer of a CNN for multi-class classification problems. It transforms the logits (raw output) into probabilities. Softmax is defined as f(x) = exp(x) / sum(exp(x)) for each element in the output vector.

Relu:
F(x) = max(0,x) Sigmoid:
F(x)=1/1+e^-x
Where f(x) represents the output value given the input x.

FLOW CHART:



CONCLUSION:

In conclusion, forecasting bankruptcy risk using deep learning can be a valuable approach for assessing the financial health of companies. By leveraging neural network models, this methodology enables the analysis of financial data to predict the likelihood of a company experiencing financial distress or bankruptcy. By employing this methodology, financial institutions, investors, and other stakeholders can make more informed decisions by assessing the bankruptcy risk of companies, aiding in risk management, investment strategies, and overall financial planning.

Results:

The results of bankruptcy risk forecasting using deep learning can vary depending on the specific dataset, model architecture, and other factors. Here are some potential outcomes and insights that can be gained from employing deep learning in bankruptcy risk prediction:

Prediction Accuracy: Deep learning models have the potential to achieve high prediction accuracy for bankruptcy risk. Feature Importance: Deep learning models can provide insights into the most influential features contributing to bankruptcy risk prediction.

Early Warning Signals: Deep learning models can potentially detect early warning signals of financial distress or bankruptcy.

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