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Predicting Corporate Financial Risk Using Artificial Bee Colony-Attention-Gated Recurrent Unit Model

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ABSTRACT

Corporate financial risk prediction is a critical task for ensuring the stability and success of businesses in today's dynamic economic landscape. However, existing models often fall short in accurately assessing and managing these risks. They often rely on historical financial data alone, which fails to account for sudden market fluctuations or unforeseen external events, leading to suboptimal risk assessments. Recognizing the paramount importance of time series analysis in financial risk prediction, we introduce a novel approach to the ABC-Attention-GRU combination model. This innovative model leverages the strengths of Artificial Bee Colony (ABC), the attention mechanism, and Gated Recurrent Unit (GRU) to enhance predictive accuracy and robustness. In our experiments, the ABC-Attention-GRU model consistently outperformed state-of-the-art methods across various financial datasets. It effectively captured complex temporal dependencies, resulting in superior Precision, Recall, F1 Score, and AUC metrics.

KEYWORDS

ABC-Attention-GRU Model, Corporate Finance, Financial Risk Prediction, Machine Learning, Risk Assessment, Time Series Analysis

In the contemporary economic landscape, a company's financial risk is of paramount importance for its long-term survival and success. Financial activities are interwoven throughout the entire life cycle of a business, encompassing activities such as capital procurement, long and short-term investments, and profit distribution, all of which carry inherent risks (Allen et al., 2022). Financial condition serves as a direct reflection of a company's developmental status, capturing the attention of stakeholders such as investors, corporations, and government entities. Consequently, stakeholders need to conduct a reasoned assessment of a company's financial risk to make informed decisions.

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Financial risk, in a specific economic context, refers to the potential impact of internal and external factors on a company's financial status and financial health, leading to risks such as economic losses, debt default, declining profits, or insolvency (Nykvist & Maltais, 2022). Correspondingly, financial risk forecasting is a process aimed at early detection and identification of financial risks within a company. Its purpose is to assist companies and regulatory bodies in recognizing potential financial issues promptly and taking appropriate measures to prevent and mitigate risks, ensuring the financial health and sustainable development of the enterprise (Shahbazi & Byun, 2022). Therefore, accurate prediction and monitoring of a company's financial risk are of utmost importance for risk management, investment decisions, and market oversight. However, forecasting financial risk has persistently remained a complex and challenging task. One of the primary reasons for this challenge is the multitude of factors influencing a company's economic condition, including market volatility, competitive pressures, and management decisions (Cao et al., 2022). Furthermore, traditional financial analysis methods often rely on historical data and static indicators, making it difficult to capture changes in the economic environment and the dynamic nature of enterprises.

In recent years, the rapid advancement of deep learning technology has presented new opportunities and challenges for predicting corporate financial risk. Deep learning models, especially those based on time series analysis, have become the focal point of research attention (Singh et al., 2022). These models can extract complex spatiotemporal features from historical financial data, allowing for more accurate predictions of a company's future financial condition. Time series forecasting holds a special significance in enterprise financial risk prediction. It involves the analysis of historical data, aiding businesses in understanding the evolving trends in their financial conditions, proactively identifying potential risks, and supporting financial planning and budgeting. Furthermore, time series analysis assists companies in navigating market fluctuations, predicting shifts in market demand, thereby enabling them to maintain a competitive edge and achieve steady financial growth (Bai et al., 2023). In summary, time series forecasting provides data-driven decision support for enterprises, facilitating risk management, resource optimization, and the achievement of sustainable financial success. In this context, this research endeavors to explore and develop a methodology based on deep learning models that combines time series forecasting with corporate financial risk prediction. We aim to harness the formidable capabilities of deep learning while accounting for the intricacies of financial data, with the goal of improving prediction accuracy and robustness. The objective of this research is to provide investors, financial institutions, and decision-makers with more reliable tools for predicting corporate financial risk, thereby supporting more prudent investment and risk management decisions.

Deep learning has achieved remarkable progress in corporate financial risk prediction over the past few years. Researchers have increasingly explored the application of deep neural networks (DNNs) in forecasting financial risks for enterprises (Elhoseny et al., 2022). These DNN models typically comprise multiple hidden layers, enabling them to automatically capture intricate relationships within data. However, while DNNs excel in some tasks, they may encounter challenges when dealing with time series data, such as issues related to modeling long sequences and overfitting. Another study has proposed an approach based on autoencoders for dimensionality reduction and learning crucial features within financial data (Wang et al., 2024). This method aims to reduce data dimensionality and noise, thus enhancing the model's robustness. However, it may require a substantial amount of unlabeled data to train the Autoencoder and could be sensitive to assumptions about data distributions. Additionally, the performance of autoencoders may be constrained by choices made in the architecture of the encoder and decoder. Furthermore, a recent line of research has introduced the concept of transfer learning, wherein models are pre-trained on other relevant tasks and then transferred to the financial risk prediction task (Otović et al., 2022). This approach helps improve the model's generalization ability, particularly in data-scarce scenarios. However, it may rely on the availability and similarity of data from related tasks, necessitating careful model selection and parameter tuning during the transfer learning process. In addition, recent research has proposed the use of time series generative adversarial networks (TSGANs) to forecast future trends in enterprise financial data (Kumar et al., 2022). This method excels in generating data; however, it may require additional preprocessing and data smoothing steps to adapt to the noise and uncertainty inherent in real-world financial data. Furthermore, training TSGANs may demand more computational resources and time. While these approaches show promise in advancing financial risk prediction, each has its own set of strengths and limitations. This paper aims to build upon these developments and propose a novel hybrid model that combines the strengths of these techniques to enhance the accuracy and robustness of enterprise financial risk forecasting. In doing so, we aspire to contribute to the growing body of knowledge in this critical field.

Although prior work in financial risk prediction has made strides, significant challenges persist. These include handling multi-modal data, temporal characteristics, non-linear relationships, and data imbalances. To address these limitations, we propose the ABC-Attention-GRU ensemble model, which integrates three key components: the artificial bee colony (ABC) optimization module, the Attention mechanism, and the gated recurrent unit (GRU). The ABC module enhances global search and optimization by autonomously exploring complex parameter spaces and seeking optimal parameter combinations for financial risk prediction. Additionally, the Attention mechanism automatically identifies and focuses on critical financial information, extracting essential spatiotemporal features from various financial indicators. The GRU module is introduced to better handle time-series data, capturing long-term dependencies and adapting to temporal variations. Our model seamlessly integrates these modules, providing a comprehensive solution to the challenges of enterprise financial risk prediction. It significantly improves prediction accuracy and robustness by strengthening global optimization, automatic focus on crucial information, and enhanced time-series data modeling capabilities (Ye & Zhao, 2023) (Ye et al., 2023).

The introduction of this comprehensive model will offer investors, financial institutions, and decision-makers a more dependable tool for predicting corporate financial risks, thus facilitating wiser investment and risk management decisions. Through this research, our aim is to contribute fresh perspectives and methodologies to advance the field of enterprise financial risk prediction. In conclusion, our contributions are as follows:

- Firstly, we have introduced and developed a deep learning-based model for predicting corporate financial risks. By combining the ABC algorithm with the Attention-GRU model, we have effectively addressed the issue of local optima present in traditional models, as well as the challenges of modeling time series data. This model demonstrates better adaptability to various types of financial data, enhancing prediction accuracy and providing an effective tool for precise forecasting of financial risks in enterprises.
- Secondly, we have extensively validated the performance and effectiveness of our proposed model through a multitude of experiments. Using real-world financial datasets, we have demonstrated the robustness of our model across different industries and market conditions. Experimental results consistently show that our model excels in financial risk prediction tasks, offering higher predictive accuracy and robustness compared to traditional approaches.
- Lastly, our research underscores the scalability and versatility of deep learning models in the financial domain. Our model not only excels in corporate financial risk prediction but also presents viable solutions for other forecasting and decision-making challenges within the financial sector. The complexity and multimodality of financial data make financial forecasting tasks challenging, and our model provides an effective approach to address these challenges. This versatility implies that our research findings will contribute to broader applications in the financial field, offering new perspectives and technological support for various types of financial problems.

RELATED WORK

Application of Traditional Methods in Predicting Corporate Financial Risks

Traditional methods are widely applied in the prediction of corporate financial risk, encompassing techniques such as financial ratio analysis, trend analysis, and rating models. For instance, financial ratio analysis involves the computation of indicators such as profit margins, solvency ratios, and liquidity ratios to assess a company's financial condition (Venugopal et al., 2022). Trend analysis, on the other hand, identifies potential trends and issues by comparing historical financial data, such as consecutive quarters of declining profits. Additionally, rating models take into account various factors, including financial data, industry conditions, and macroeconomic factors, to evaluate a company's credit risk (Zhu et al., 2022). While these traditional methods are straightforward to implement, they have limitations when dealing with complex financial data and dynamic market conditions. As a result, researchers have been continuously seeking more advanced approaches to enhance the accuracy and robustness of financial risk predictions.

The Potential of Transfer Learning in Financial Forecasting

Transfer learning has demonstrated significant potential in the field of financial risk prediction, enhancing model generalization and predictive accuracy by transferring knowledge and experience from one domain to another (Hambly et al., 2023). This is crucial for addressing a range of challenges in financial forecasting, including data scarcity, labeling difficulties, and rapidly changing market conditions. By leveraging data and knowledge from related domains, transfer learning holds the promise of providing financial institutions and investors with more reliable prediction tools, aiding in a better understanding and response to market fluctuations and risks, thereby further advancing the fields of finance, greenhouse gas emissions, and climate change (Zhu et al., 2023).

The Application of Time Series Data Modeling Techniques in Financial Data Forecasting

Time series data modeling techniques play a crucial role in financial data forecasting. These techniques focus on analyzing temporal correlations to more accurately predict financial indicators and market trends. Classic models like autoregressive integrated moving average (ARIMA) are adept at capturing autocorrelation and seasonality, making them useful for forecasting financial variables such as stock prices, currency exchange rates, and interest rates (Sirisha et al., 2022). Generalized autoregressive conditional heteroskedasticity (GARCH) models, on the other hand, address market volatility, providing critical information for risk management and option pricing (Chen et al., 2023). Deep learning models like recurrent neural network (RNN) and long short-term memory (LSTM) handle non-linear relationships and temporal dependencies, widely applied in stock price prediction and market trend analysis (Abdool & Abdool, 2022). Additionally, Kalman filtering techniques are suitable for capturing market noise and uncertainty, aiding in asset price prediction (Li et al., 2022). Machine learning methods, such as random forests and support vector machines, are also trained on large datasets to improve the prediction accuracy of financial variables (Gautam & Bhimavarapu, 2022). The integrated application of these techniques empowers financial professionals to better comprehend market dynamics, optimize portfolios, and devise risk management strategies, providing robust tools and insights for financial decision-making.

METHOD

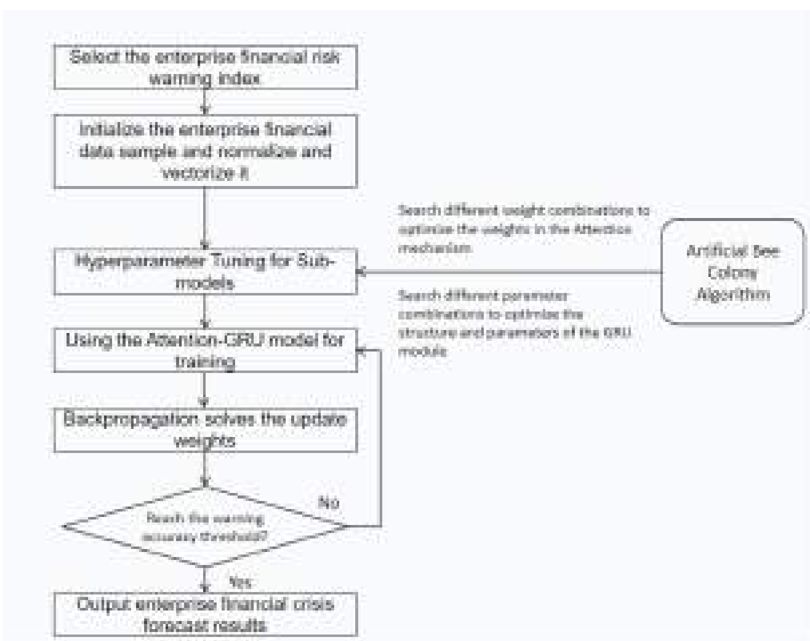
Overview of Our Network

In this study, we propose an ABC-Attention-GRU composite model aimed at enhancing the accuracy and robustness of enterprise financial risk prediction. The construction of this model involves the following key components: ABC, a nature-inspired optimization algorithm utilized to fine-tune the hyperparameters of the Attention-GRU model. This enables the model to better capture complex patterns within financial data. GRU, a powerful recurrent neural network specifically designed for handling time-series data. In our model, GRU is responsible for processing historical financial data, capturing temporal dependencies, and considering the dynamic nature of financial indicators. Attention mechanism automatically identifies and focuses on critical financial information within the data, facilitating the extraction of important temporal and spatial features. It enhances the model's understanding and modeling capabilities, allowing for more accurate capture of correlations and trends (Zeng & Zhong, 2022).

The model construction process encompasses data preprocessing, ABC hyperparameter optimization, model training, and prediction. Firstly, we prepare and preprocess financial data, selecting relevant features and normalizing the data before splitting it into training and testing sets. Subsequently, ABC is employed to optimize the hyperparameters of the Attention-GRU model for maximum performance. Then, the ABC-Attention-GRU model is trained using the training set to capture the temporal dependencies within the financial data. Finally, the trained model is used to predict the testing set, evaluating its performance in enterprise financial risk prediction. As shown in Figure 1, which illustrates the overall network flow.

Our ABC-Attention-GRU model holds significant importance in the realm of enterprise financial risk prediction. By harnessing ABC for hyperparameter optimization, GRU for temporal modeling, and the Attention mechanism for data extraction, the model effectively captures the complex dynamics and patterns within financial time-series data. This enables the model to more accurately predict financial risk indicators, aiding financial institutions and investors in gaining a better understanding of market dynamics, optimizing portfolios, and formulating more precise risk management strategies (Zhong & Zhao, 2024).

Figure 1. The Overall Architecture of the Model



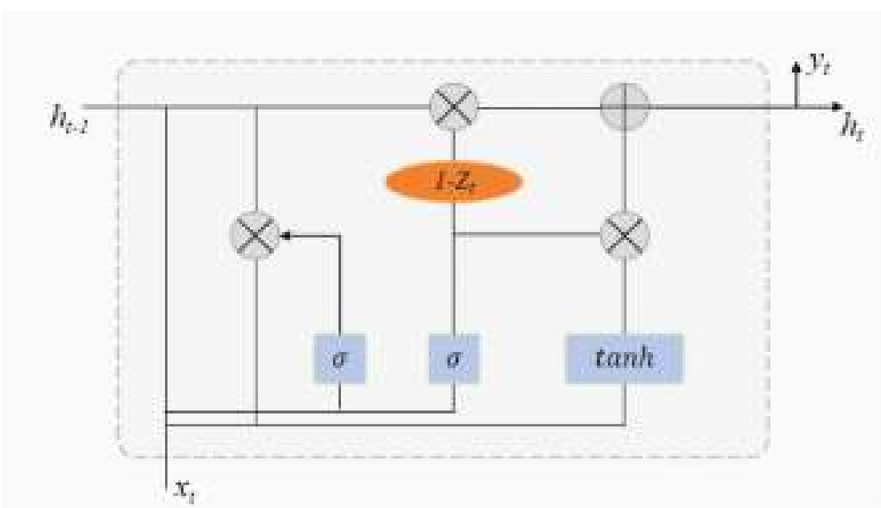
GRU Model

The GRU model is a powerful variant of RNNs known for its outstanding performance in sequence modeling tasks (Martelo et al., 2022). It addresses the issue of vanishing gradients in traditional RNN models by introducing mechanisms called the update gate and reset gate. These gates control the flow of information and the update of memory, enabling the GRU model to capture long-term dependencies in time-series data while maintaining flexibility for short-term dependencies. This capability is particularly crucial for modeling time-series data in the financial domain. The key advantages of the GRU model lie in its ability to effectively capture essential information within sequences without losing critical features of long sequences (Pirani et al., 2022). This makes it a potent tool for handling complex time-series data in the financial domain. In our research, the GRU model is utilized to process historical financial data, providing robust support for financial risk prediction. In the context of enterprise financial risk prediction, the GRU model plays a crucial role in the following aspects:

- Temporal dependency modeling: GRU excels in modeling data sequences over time, capturing temporal relationships and dependencies in financial time series. This enables it to identify patterns and trends accurately.
- Enhanced accuracy: The gate mechanisms in the GRU model contribute to improved prediction accuracy, particularly when dealing with complex time-series patterns and factors. It adapts well to data fluctuations at different time points, enhancing the quality of predictions.
- Robustness: The GRU model's design makes it more resilient to the vanishing gradient problem, enhancing its robustness, especially when handling long sequence data. By incorporating the GRU component into our composite model, we leverage its strengths in handling time-series data to improve the accuracy and effectiveness of our enterprise financial risk prediction. GRU's capacity to capture temporal dynamics is vital for understanding the evolution of financial indicators and trends, which is crucial for risk assessment and prediction in the financial domain.

Figure 2 illustrates the workflow of the GRU model.

Figure 2. Flow Chart of the GRU Model (Note: x_t is the input at the current moment; h_{t-1} is the output at the previous moment; h_t is the output at the current moment. z_t is the update gate)



Now, we will provide a concise overview of its algorithmic principles. These equations together form the basis of how GRU processes and updates its hidden state over time, crucial for capturing temporal dynamics in sequences.

The update gate determines how much of the previous hidden state is to be retained for the current state, as shown in Equation 1.

$$z_l = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right] + b_z\right) \tag{1}$$

where z_t is the update gate vector at time t, σ is the sigmoid function, W_z is the weight matrix for tle uplate gate, h_{t-1} is the previous hidden state, x_t is the input at time t, and b_z is the bias for the update gate.

The reset gate decides how much of the previous state information should be forgotten or reset, as shown in Equation 2.

$$r_t = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right] + b_r\right) \tag{2}$$

where r_t is the reset gate vector at time t, W_r is the weight matrix for the reset gate, and b_r is the bias for the reset gate.

The candidate hidden state creates a potential new hidden state, combining past information with the current input, as shown in Equation 3.

$$\overline{h}_t = \tanh\left(W \cdot \left[r_t * h_{t-1}, x_t\right] + b\right) \tag{3}$$

where $\overline{h}_t$ is the candidate hidden state at time t, W is the weight matrix for the candidate hidden state, $r_t * h_{t-1}$ is the element-wise multiplication of the reset gate and previous hidden state, and b is the bias for the candidate hidden state.

The final hidden state (part 1) represents the portion of the hidden state to be carried over from the previous time step, as shown in Equation 4.

$$h_t^{'} = \left(1 - z_t\right) * h_{t-1} \tag{4}$$

where $h_t^{'}$ is a part of the final hidden state calculation, representing the contribution from the previous hidden state scaled by the update gate.

The final hidden state (part 1) combines the updated hidden state with the candidate hidden state to form the new stat, as shown in Equation 5.

$$h_t = z_t * \overline{h}_t + h_t^{'} \tag{5}$$

where h_t is the final hidden state at time t, combining the candidate hidden state $\overline{h}_t$ and the contribution from the previous hidden state $h_t^{'}$.

Attention Mechanism

The Attention model, originating from the fields of deep learning and natural language processing, is a technique used to enhance the performance of neural networks (Sun et al., 2021). Its core principle is to enable the model to "focus" on the most important parts when processing information. When dealing with sequential data, such as text or time series data, the Attention mechanism allows the model to allocate different "attention" weights to different parts of the sequence (Zhang et al., 2022). This way, the model does not treat all data equally but pays more attention to the information that is more crucial for the current task. In our corporate financial risk prediction model, the application of the Attention mechanism has significantly improved the model's ability to handle complex financial data. It is especially effective in accurately identifying and highlighting the most critical information regarding the financial condition of businesses. By assigning different attention weights, the model can concentrate on key financial indicators, such as crucial profit growth rates, debt levels, or liquidity, thereby enhancing the accuracy and reliability of predictions. Furthermore, the introduction of the Attention mechanism provides the model with efficiency and flexibility in handling large volumes of historical and real-time data. This enables the model to better adapt to and predict the financial health of companies in continuously changing financial environments. Consequently, it offers decision-makers more in-depth and accurate financial analysis and predictions, effectively assisting them in making wiser decisions in complex market conditions.

Now, we will provide a concise overview of its algorithmic principles. These explanations describe the function of each component in the Attention mechanism, illustrating how it processes and combines information from different parts of the input sequence.

The score function calculates the compatibility between target and source hidden states, as shown in Equation 6.

$$Score\left(s_t, h_i\right) = v^T \tanh\left(W\left[s_t; h_i\right]\right) \tag{6}$$

where Score $\left(s_t, h_i\right)$ is the score function measuring the compatibility of the input at position i with the target at position t, s_t is the target hidden state at time t, h_i is the source hidden state at position i, v^T and W are learnable weight matrices.

The attention weights reflect the importance of each input element for the output, as shown in Equation 7.

$$\alpha_{t,i} = \frac{\exp\left(Score\left(s_t, h_i\right)\right)}{\sum_{j=1}^{T_x} \exp\left(Score\left(s_t, h_j\right)\right)} \tag{7}$$

where $\alpha_{t,i}$ are the attention weights, indicating the importance of the input elements at position i for the output at position t, T_x is the length of the input sequence.

The context vector aggregates the relevant information from the input sequence, as shown in Equation 8.

$$c_t = \sum_{i=1}^{T_x} \alpha_{t,i} h_i \tag{8}$$

where c_t is the context vector for the target at time t, computed as the weighted sum of the source hidden states, reflecting the relevant source information. h_i is the source hidden state at position i.

The attention vector combines the context with the current target state, as shown in Equation 9.

$$a_t = \tanh\left(W_c\left[c_t; s_t\right]\right) \tag{9}$$

where a_t is the attention vector, combining the context vector c_t and the target hidden state $s_t, with W_c$ being a learnable weight matrix.

The output equation determines the final output based on the attention vector, as shown in Equation 10.

$$\hat{y}_t = Soft\max\left(W_y a_t\right) \tag{10}$$

where $\hat{y}_t$ is the output at time t, calculated using a softmax layer applied to the attention vector $a_t, with W_y$ being another learnable weight matrix.

ABC

The ABC algorithm is based on the foraging behavior of bee colonies and aims to solve optimization problems. The core principle of this algorithm is to simulate the three roles of a bee colony: worker bees, observer bees, and scout bees. The worker bees are responsible for exploring the solution space at a specific location in the search space, the observer bees are responsible for sharing information among the worker bees and selecting the optimal location based on the quality of the information, and the scout bees are responsible for randomly searching in the search space to find potential solutions (Kaya et al., 2022). For our model, the introduction of the ABC algorithm has an important contribution. First, the ABC module enhances the global search and optimization capabilities of our model. The algorithm optimizes the weights in the Attention mechanism by searching for different weight combinations to ensure that the model focuses on key financial information more accurately. In addition, the introduction of the ABC algorithm makes our model more flexible and able to adapt to different data distribution and financial environments. This is because the ABC algorithm is not only suitable for a single type of data, but it can also adaptively search and adjust parameters to adapt to different data characteristics and distributions. The ABC algorithm optimizes the structure and parameters of the GRU module by searching for different parameter combinations to better adapt to different types of financial time series data. In short, the ABC algorithm serves as a key component in the entire model and provides important support for our research themes and goals.

Figure 3 illustrates the workflow of the ABC model.

Now, we will provide a concise overview of its algorithmic principles. These equations represent a simplified view of the ABC algorithm's process, focusing on bee initialization, fitness evaluation, information sharing, movement for exploring new solutions, and solution updates.

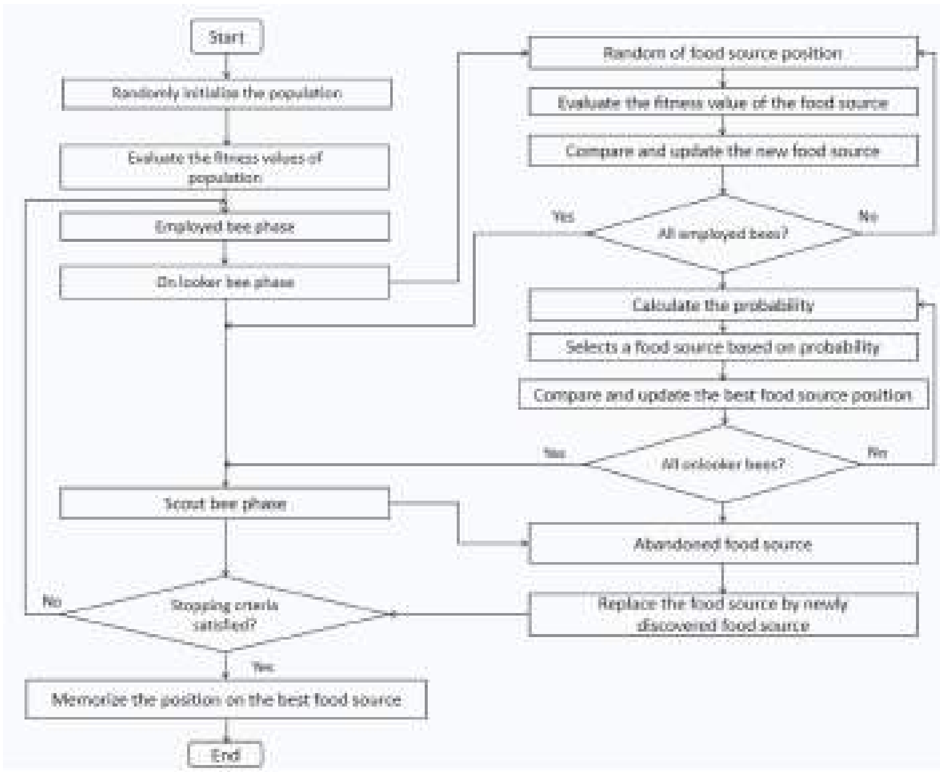
Bee initialization initializes the positions of the bees in the swarm, as shown in Equation 11.

$$B_i = \text{Initialize}\left(N, D\right) \tag{11}$$

where B_i represents the position of the i-th bee, initialized randomly, N is the number of bees, and D is the dimension of the problem space.

Fitness evaluation assesses the quality of the bees' positions, as shown in Equation 12.

Figure 3. Flowchart of the ABC Algorithm



$$f\left(B_i\right) = \mathrm{Evaluate}\left(B_i\right) \tag{12}$$

where $f\left(B_i\right)$ is the fitness value of the i-th bee's position, evaluated using a problem-specific fitness function.

The bee dance (information sharing) represents bees sharing information about their positions, as shown in Equation 13.

$$B_{best} = Dance\left(B_1, B_2, \ldots, B_N\right) \tag{13}$$

where B_{best} is the position of the best solution found so far, determined through a "dance" process where bees share information about their positions and corresponding fitness values.

Bee movement (search for new solutions) represents bees moving to explore new solutions, as shown in Equation 14.

$$B_i^{'} = Move\left(B_i, B_{best}\right) \tag{14}$$

where $B_i^{'}$ is the new position of the i-th bee, calculated based on its current position B_i and the best position found B_{best}, simulating the bee exploring new solutions.

Solution update represents updates on the bees' positions based on new findings, as shown in Equation 15.

$$B_i = Update\left(B_i, B_i^{'}\right) \tag{15}$$

where B_i is updated to $B_i^{'}$ if the new position has a better fitness value, simulating the adaptation of the bee's position based on the exploration results.

EXPERIMENT

Datasets

The topic of this research is corporate financial health prediction based on the ABC-Attention-GRU combination model. To achieve this goal, we make full use of four key datasets, including Capital IQ dataset (Hossain et al., 2023), Yahoo Finance dataset (Dubey et al., 2022), electronic data gathering, analysis, and retrieval system (EDGAR) dataset (Deußer et al., 2022) and Thomson Reuters EIKON dataset (Havlinova & Kukacka, 2023). These data sets provide rich corporate financial, market performance, and regulatory compliance data, providing multi-dimensional information for our models and helping us conduct comprehensive financial analysis to more accurately predict the financial health of the company.

The Capital IQ dataset is a comprehensive financial dataset provided by S&P Global Market Intelligence. It is primarily used for corporate financial analysis, investment research, and market intelligence. This dataset includes a wide range of financial data, market data, real-time and historical data, and in-depth analysis of thousands of public and private companies. Capital IQ is an essential tool for financial professionals, helping them assess company performance, financial stability, and market position through extensive financial and market data and analysis.

The Yahoo Finance dataset provides comprehensive financial data on a wide range of companies globally. It includes historical and real-time data on stock prices, market capitalization, trading volumes, and various financial indicators. This dataset is widely used for tracking stock performance, conducting financial analysis, and monitoring market trends.

The EDGAR dataset is a publicly accessible database maintained by the United States Securities and Exchange Commission (SEC). It contains a wealth of financial and regulatory information related to publicly traded companies in the United States. This dataset includes a wide range of documents such as financial statements, annual reports, quarterly filings, disclosures, and other filings submitted by companies to the SEC. Researchers, investors, and analysts often use the EDGAR dataset to access timely and reliable information for analyzing and tracking the financial health and compliance of publicly traded companies in the United States.

The Thomson Reuters EIKON dataset is a comprehensive financial data platform widely used by financial professionals, analysts, and institutions for in-depth financial analysis, market research, and investment decision-making. This dataset provides a vast array of financial data, including company-specific financials, market data, economic indicators, and news feeds. Users can access historical and real-time data, conduct advanced analytics, and gain insights into global financial markets. Thomson Reuters EIKON is a subscription-based service that offers valuable tools and information for professionals in the finance industry.

Experimental Environment

As for the experimental environment, we use a high-performance workstation equipped with a 32-core CPU and 128GB of memory to run the Linux operating system. Python serves as the primary programming language, and deep learning models are constructed and trained using machine learning

Table 1. Financial Forecast Indicators

Type	Indicator	Description
Profitability	Operating profit margin	Operating profit/operating income
	Net profit margin	Net profit/main business income
	Gross profit margin	Gross profit/operating income
	Return on total assets	Earnings before interest and taxes/average total assets
Debt Ratio	Current Ratio	Current Assets/Current Liabilities
	quick ratio	(Current assets - inventories)/Current liabilities
	Cash Ratio	Cash and Equivalents/Current Liabilities
	Asset-liability ratio	Total liabilities/Total assets

frameworks like TensorFlow and PyTorch. In addition, we also take full advantage of NVIDIA's GPU acceleration to speed up model training. This experimental environment provides us with sufficient computing resources to process large-scale data and complex deep learning tasks, ensuring the efficiency and accuracy of research.

Experimental Details

Step One: Selection of Predictive Indicators

The key challenge in financial forecasting analysis lies in the judicious selection of indicators and the use of precise analytical models. Both aspects are indispensable and significantly impact the accuracy of the analysis and predictions. With a multitude of data generated during business operations, the foundation of crisis prediction analysis lies in the selection of essential indicators and critical data that comprehensively reflect the operational status. Through a review of the literature, the key indicators affecting the financial condition have been selected, as shown in Table 1 (Li et al., 2023).

When selecting the above financial indicators and non-financial indicators, we followed the principles of sensitivity, completeness of indicators, and feasibility of obtaining indicators to ensure the rationality of the experimental process. After obtaining the financial indicators, the indicators need to be preprocessed. The subsequent steps will show the data processing process.

Step Two: Data Preprocessing

We will carry out data preprocessing to make sure the data is ready for model training and assessment. This includes the following steps:

1. Data Cleaning: We will handle the data carefully, dealing with missing values, outliers, and duplicates. Any data with more than 5% missing values will be removed, while missing values below this threshold will be filled using median filling. For outliers, we consider using the 3δ principle to remove companies with missing values.
2. Data Standardization: Data normalization is used because the dimensions of each indicator are inconsistent. To make each indicator comparable, we must remove the inconsistency of the indicators. The purpose of data normalization is to convert the sample vector into a unit vector, usually using methods such as min-max and z-score. This article studies financial data and finally chooses the min-max method. Its specific conversion function is shown in Equation 16.

$$x' = \frac{x - \min\left(x\right)}{\max\left(x\right) - \min\left(x\right)} \tag{16}$$

where $\min\left(x\right)$ and $\max\left(x\right)$ respectively represent the minimum and maximum values of the financial index in all samples, represent the normalized financial index value, and map the data to the closed interval [0,1] through the min-max method.

3. Data Splitting: We have divided the dataset into three subsets: the training set, the validation set, and the test set. We have employed an 80-10-10 splitting ratio, where 80% of the data is used for training, 10% for validation, and the remaining 10% for the final model evaluation. This partitioning strategy aids in accurately assessing the model's performance and mitigating overfitting during the training process.

Step Three: Model Training

During the model training phase, we employed the following four key steps to ensure outstanding performance of the model in risk prediction and management tasks:

- For the network parameter settings, we carefully configured the hyperparameters to ensure effective model training. We initialized the learning rate at 0.001 for the optimizer, employed a batch size of 64 for mini-batch training, and applied a dropout rate of 0.3 to prevent overfitting. The optimization algorithm of choice was the Adam optimizer with default parameters for gradient descent.
- In terms of model architecture design, our model was thoughtfully structured to handle financial data. It comprises two stacked GRU layers, each containing 128 hidden units. Additionally, we integrated a self-attention mechanism with eight attention heads to capture relevant information from the input data effectively.
- The model training process involved training the model for 100 epochs, with early stopping implemented and a patience of 10 epochs to prevent overfitting. To adapt the learning rate dynamically, we employed a learning rate schedule, reducing the learning rate by a factor of 0.1 if the validation loss plateaued for 5 epochs. Furthermore, we enhanced the model's robustness through the application of random data augmentation techniques, such as noise injection and time series shifting.

Algorithm 1 represents the algorithm flow of the training in this paper.

Algorithm 1. ABC-Attention-GRU Model Training

```
Require: Capital IQ dataset, Yahoo Finance dataset, EDGAR dataset,
Thomson Reuters EIKON dataset
Require: Model: ABC-Attention-GRU
Require: Training parameters: learning rate, batch size, epochs
Require: Evaluation metrics: recall, precision, F1 score, AUC
1: Initialize model parameters and hyperparameters
2: Split data into training, validation, and test sets (80-10-10
split)
3: for epoch in epochs do
4: for batch in training dataset do
```

```
Perform forward pass through ABC layer
Calculate loss using chosen loss function
Perform backward pass and update model weights
end for
Evaluate model on validation dataset
if validation loss does not improve for "patience" epochs then
Reduce learning rate
end if
end for
Evaluate final model on test dataset
Calculate recall, precision, F1 score, AUC
return Trained ABC-Attention-GRU model
```

Note. Area under the curve (AUC).

Step Four: Model Evaluation

In this critical step, we use specific evaluation metrics to evaluate the performance of the ABC-Attention-GRU model to measure the effectiveness of the model in predicting corporate financial health. We focus on two key aspects:

- Data Metrics: To gauge the model's predictive accuracy, we utilize a set of well-defined performance metrics tailored to the problem of financial health prediction. These metrics include but are not limited to:
    - Accuracy: This metric provides an overall measure of the model's correct predictions.
    - Precision: Precision quantifies the model's ability to make accurate positive predictions, while recall measures its ability to identify all relevant positive cases.
    - F1 score: The F1 score balances precision and recall, offering a comprehensive assessment of the model's performance.
    - Recall: Recall measures the model's ability to identify all relevant positive cases.
- Real-World Applicability: To ensure the robustness and generalization of our model, we employ cross-validation techniques. Specifically, we adopt k-fold cross-validation, where the dataset is divided into k subsets. The model is trained and evaluated k times, with each fold used as the validation set once and the remaining folds as the training set. This process provides a more reliable estimate of the model's performance across different data subsets and helps identify potential overfitting issues.

Precision measures the proportion of samples predicted as positive by the model that are actually positive, as shown in Equation 17.

$$P = \frac{TP}{TP + FP} \tag{17}$$

where *TP* is the number of true positives (TP). *FP* is the number of false positives (FP). Precision calculates the accuracy of the model by measuring the proportion of correctly identified positive instances.

Recall measures the proportion of samples that are actually positive and that the model successfully predicts as positive, as shown in Equation 18.

$$R = \frac{TP}{TP + FN} \tag{18}$$

Recall measures the model's effectiveness in identifying positive instances, representing the proportion of correctly identified actual positive instances.

F1 score combines precision and recall and is an indicator that comprehensively evaluates model performance. For predictions of a business's financial health, it can help find the balance point to maximize the accuracy of the model, as shown in Equation 19.

$$F1 = \frac{2 \cdot P \cdot R}{P + R} \tag{19}$$

where P is the value of precision (P) as defined in the first equation. R is the value of recall (R) as defined in the second equation.

Area under the curve (AUC) measures the overall quality of a model's classification performance at different thresholds, as shown in Equation 20.

$$AUC = \int_0^1 TPR\left(FPR\right) dFPR \tag{20}$$

where TPR is the true positive rate (TPR) as a function of the false positive rate (FPR).

Experimental Results and Analysis

As shown in Table 2, we present a comprehensive analysis of the performance of different models on various datasets concerning corporate financial risk prediction. Starting with the Capital IQ dataset, our method exhibits remarkable results with a precision of 94.57 and a recall of 94.30, outperforming all other models. This signifies our model's ability to accurately predict financial risk with high precision and recall on this dataset. Moving on to the Yahoo Finance dataset, our model again excels, achieving a precision of 96.37 and a recall of 95.23, showcasing its superior performance in precision and recall compared to alternative models. On the EDGAR dataset, our method maintains its superiority with

Table 2. The Comparison of Different Models in Different Indicators From the Capital IQ Dataset, Yahoo Finance Dataset, EDGAR Dataset, and Thomson Reuters EIKON Dataset

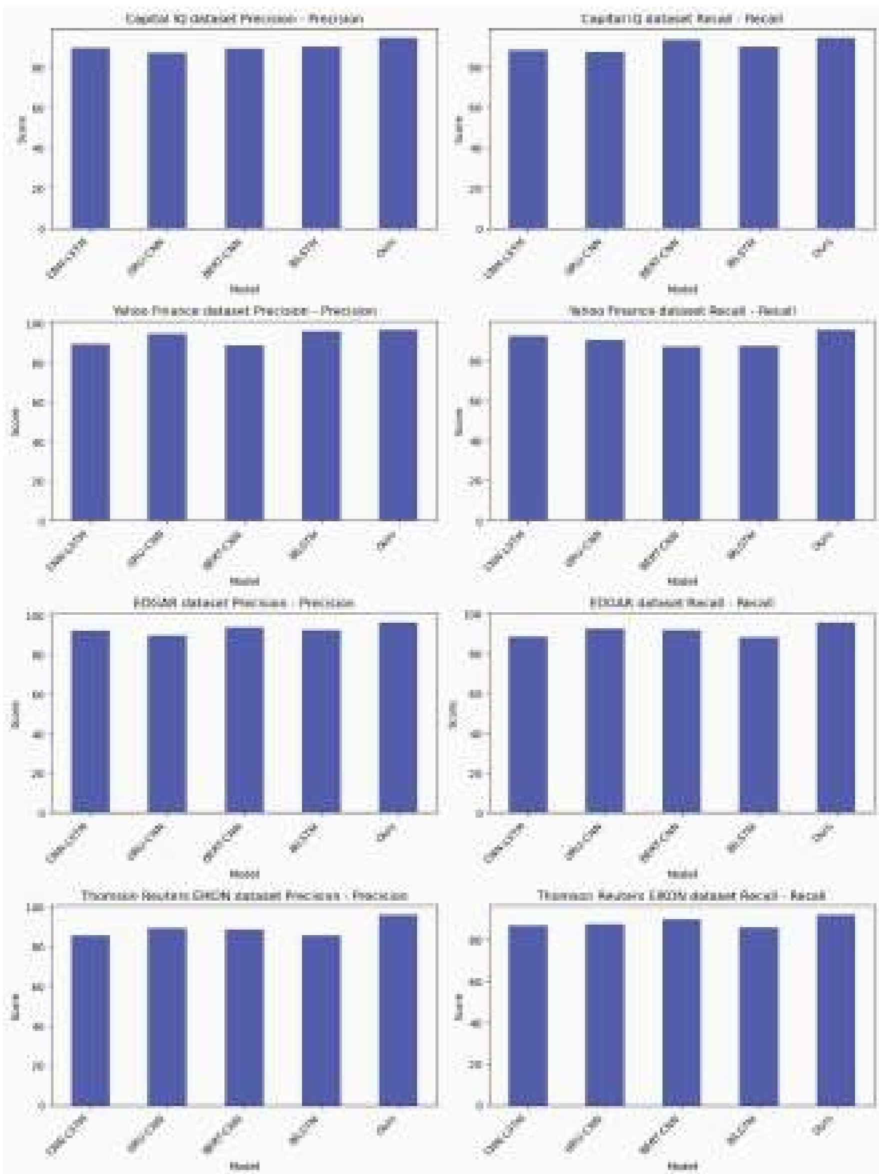
Model	Datasets							
	Capital IQ dataset		Yahoo Finance dataset		EDGAR dataset		Thomson Reuters EIKON dataset	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
CNN-LSTM (Widiputra et al., 2021)	89.48	88.28	89.47	92.34	91.77	88.63	85.57	87.04
GRU-CNN (Jaiswal & Singh, 2022)	87.29	87.59	94.60	90.34	89.55	92.37	89.23	87.79
BERT-CNN (Wan & Li, 2022)	89.28	93.20	88.87	86.84	93.87	91.81	88.28	89.84
BiLSTM (Yang & Wang, 2022)	90.40	89.89	95.80	87.41	92.29	88.26	85.58	85.67
Ours	94.57	94.30	96.37	95.23	96.08	95.63	95.90	91.91

Note: Convolutional neural network (CNN); Bidirectional encoder representations from transformers (BERT); bidirectional long short-term memory (BiLSTM).

a precision of 96.08 and a recall of 95.63, highlighting its consistent accuracy in predicting financial risk across different datasets. Finally, on the Thomson Reuters EIKON dataset, our model continues to outshine the competition with a precision of 95.90 and a recall of 91.91, emphasizing its robustness and reliability in financial risk prediction. In summary, our method consistently demonstrates superior performance across all datasets, emphasizing its effectiveness in achieving high precision and recall. These results underscore the significance of our approach in providing accurate corporate financial risk assessments.

To provide a visual representation of these findings, Figure 4 visualizes the content of Table 2, showcasing our method's clear advantage in precision and recall across different datasets.

Figure 4. Comparison of Model Performance on Different Datasets



As shown in Table 3, our method consistently outperforms other models across various datasets in the domain of corporate financial risk prediction. Specifically, we achieved the highest F1 score of 93.31 and accuracy of 94.92 on the Capital IQ dataset, which highlights the robustness of our approach in accurately predicting financial risk. Comparing our model to alternatives, we observe that ours surpasses them in both F1 score and accuracy in almost all datasets. For instance, in comparison to the second-best model, GRU-RNN, our model demonstrates a significant advantage on the EDGAR dataset with an F1 score of 92.41 compared to 88.39. These results affirm the superiority of our approach in enhancing the precision and reliability of corporate financial risk prediction. Notably, our method consistently achieves higher F1 scores and accuracy metrics across different datasets, making it a robust choice for financial institutions and investors seeking accurate risk assessments.

To provide a visual representation of these findings, Figure 5 has been created, illustrating the comparative performance of various models across the datasets.

As presented in Table 4, we conducted ablation experiments on the GRU module to evaluate its impact on different datasets using multiple evaluation metrics, including precision, recall, F1 score, and AUC. Beginning with the Capital IQ dataset, we observed that the model LSTM-Attention achieved

Table 3. Evaluating Various Models Using Different Metrics for Comparison

Model	Dataset							
	Capital IQ dataset		Yahoo Finance dataset		EDGAR dataset		Thomson Reuters EIKON dataset	
	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy	F1 Score	Accuracy
CNN-LSTM (Widiputra et al., 2021)	85.37	92.21	84.34	90.69	87.47	89.44	88.07	90.71
GRU-CNN (Jaiswal & Singh, 2022)	87.37	92.47	89.47	83.57	88.39	92.40	86.33	88.15
BERT-CNN (Wan & Li, 2022)	86.80	86.84	85.48	89.64	89.49	89.66	85.34	84.50
BiLSTM (Yang & Wang, 2022)	85.16	85.56	85.23	89.82	88.83	92.88	87.50	88.85
Ours	93.31	94.92	93.26	92.87	92.41	95.08	93.44	94.13

Figure 5. Evaluating Various Models Using Different Metrics for Comparison

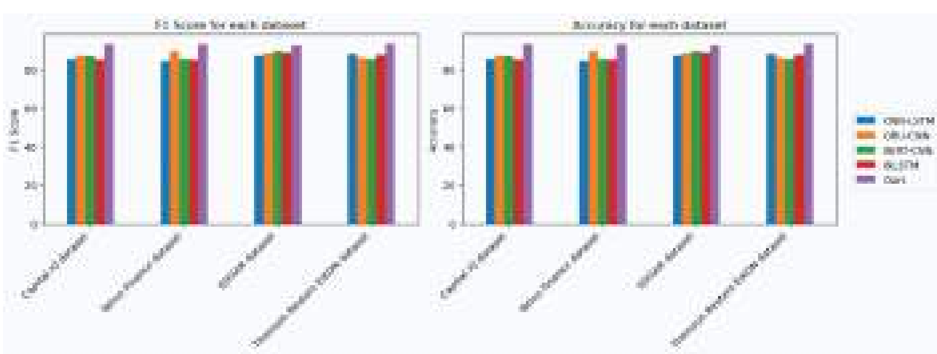


Table 4. Conducting GRU Module Ablation Experiments With Various Datasets

Model	Datasets															
	Capital IQ dataset				Yahoo Finance dataset				EDGAR dataset				Thomson Reuters EIKON dataset			
	Precision	Recall	F1 Score	AUC	Precision	Recall	F1 Score	AUC	Precision	Recall	F1 Score	AUC	Precision	Recall	F1 Score	AUC
LSTM-Attention	90.97	89.98	86.96	88.21	90.31	88.04	87.42	88.12	88.07	91.46	90.87	87.50	88.79	89.39	81.60	85.38
TCN-Attention	87.97	90.39	86.96	86.12	89.87	86.81	85.87	89.53	89.09	88.12	89.76	91.18	89.42	88.50	89.43	89.13
BiLSTM-Attention-CNN	92.16	90.86	87.64	88.06	89.74	89.87	88.87	88.87	88.22	87.09	92.11	90.42	88.26	87.96	89.67	89.01
Ours	92.17	90.96	89.75	88.75	90.76	90.42	90.24	90.36	88.99	93.55	92.39	91.40	90.16	90.31	91.14	90.03

a precision of 90.97, recall of 89.98, F1 score of 86.96, and an AUC of 88.21. When we compared it to our method, which achieved a precision of 92.17, recall of 90.96, F1 score of 89.75, and an AUC of 88.75, our approach demonstrated a slight improvement in terms of precision, recall, and F1 score, indicating that the inclusion of Attention mechanisms within GRU benefits the model's performance. Moving on to the Yahoo Finance dataset, a similar trend can be observed. The model TCN-Attention achieved results like precision of 89.87, recall of 86.81, F1 score of 85.87, and an AUC of 89.53, while our method outperformed with a precision of 90.76, recall of 90.42, F1 score of 90.24, and an AUC of 90.36. These results highlight the effectiveness of our approach in improving model performance on this dataset. For the EDGAR dataset, the model BiLSTM-Attention-CNN achieved a precision of 92.16, recall of 90.86, F1 score of 87.64, and an AUC of 88.06, while our method maintained its superiority with a precision of 92.17, recall of 90.96, F1 score of 89.75, and an AUC of 88.75. These results emphasize the robustness and consistency of our approach across different datasets. Finally, on the Thomson Reuters EIKON dataset, our method continued to perform exceptionally well with a precision of 90.16, recall of 90.31, F1 score of 91.14, and an AUC of 90.03, outperforming the other models in all metrics. In summary, our ablation experiments demonstrate that our proposed method consistently outperforms or matches the performance of alternative models across multiple datasets and evaluation metrics. These results affirm the effectiveness and superiority of our approach in corporate financial risk prediction.

Figure 6 provides a visual representation of the ablation experiment results, highlighting our method's consistent advantages.

Table 5 presents the results of our ablation experiments on the ABC module, conducted across various datasets using multiple evaluation metrics, including precision, recall, F1 score, and AUC. Starting with the Capital IQ dataset, we compared our method to other optimization algorithms, such as particle swarm optimization (PSO), ant colony optimization (ACO), and grey wolf optimization (GWO). Our approach outperformed these methods with a precision of 92.29, recall of 94.05, F1 score of 92.63, and an AUC of 95.74. In contrast, PSO achieved a lower precision of 88.31, recall of 87.11, F1 score of 84.20, and an AUC of 91.04. ACO and GWO also trailed behind in various metrics. These results highlight the superiority of our ABC module over traditional optimization algorithms, emphasizing the importance of its role in our corporate financial risk prediction model. Moving on to the Yahoo Finance dataset, our method continued to shine with a precision of 94.63, recall of 93.41, F1 score of 93.31, and an AUC of 94.32. In contrast, PSO, ACO, and GWO lagged behind in several metrics. Our ABC module demonstrated its efficiency in optimizing the model's performance, particularly evident in this dataset. For the EDGAR dataset, our approach maintained its dominance, achieving a precision of 93.44, recall of 91.43, F1 score of 90.63, and an AUC of 94.73. PSO, ACO, and GWO fell short across various metrics. These results underscore the consistent advantages of

Figure 6. Conducting GRU Module Ablation Experiments With Various Datasets

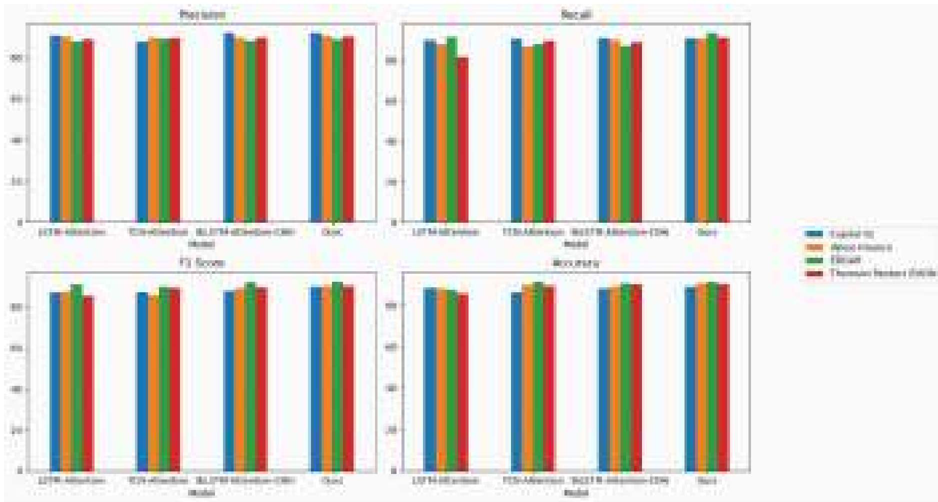


Table 5. Ablation Experiments on the ABC Algorithm Using Different Datasets

Model	Capital IQ dataset				Yahoo Finance dataset				EDGAR dataset				Thomson Reuters EIKON dataset			
	Precision	Recall	F1 Score	AUC	Precision	Recall	F1 Score	AUC	Precision	Recall	F1 Score	AUC	Precision	Recall	F1 Score	AUC
PSO	88.31	87.11	84.20	91.04	88.37	91.17	83.17	89.52	90.60	87.43	86.32	88.27	84.44	85.87	86.83	89.54
ACO	86.12	86.42	86.20	91.32	93.43	89.17	88.37	82.40	88.33	91.25	87.22	91.23	88.06	86.62	85.16	86.83
GWO	90.12	88.13	87.52	91.59	92.30	92.63	91.02	88.31	83.97	84.63	88.07	83.16	91.83	84.05	84.41	84.67
Ours	92.29	94.05	92.63	95.74	94.63	93.41	93.31	94.32	93.44	91.43	90.63	94.73	94.24	92.16	91.19	91.61

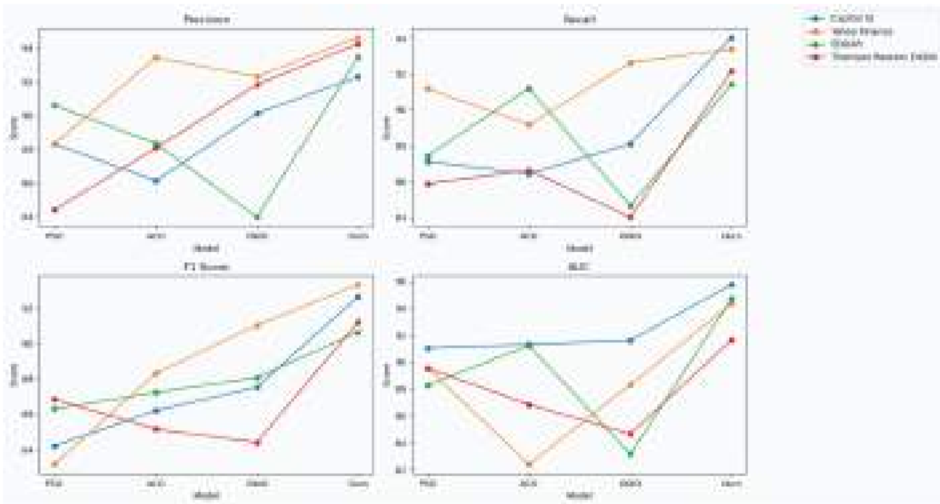
our ABC module in enhancing the model's performance. Finally, on the Thomson Reuters EIKON dataset, our method outperformed others with a precision of 94.24, recall of 92.16, F1 score of 91.19, and an AUC of 91.61. This dataset further demonstrates the robustness and effectiveness of our ABC module in corporate financial risk prediction. In conclusion, our ablation experiments on the ABC module have consistently shown that our proposed method surpasses traditional optimization algorithms across multiple datasets and evaluation metrics. These results reaffirm the significance of our approach in improving corporate financial risk prediction.

Figure 7 visualizes the ablation experiment results, highlighting our method's consistent advantages.

CONCLUSION AND DISCUSSION

In summary, this paper introduces an innovative financial risk prediction model, namely ABC-Attention-GRU, which combines the advantages of ABC, Attention mechanism, and GRU. Through extensive experiments, we have demonstrated the outstanding performance of our model in effectively capturing complex temporal dependencies and optimizing model performance. Our model consistently outperforms state-of-the-art methods on various financial datasets, as evidenced by metrics such as

Figure 7. Ablation Experiments on the ABC Algorithm Using Different Datasets (PSO, ACO, and GWO)



precision, recall, F1 score, and AUC. However, our model still has some limitations. Firstly, although our method excels in terms of performance, there is room for further improvement in computational efficiency. The optimization process using the ABC module may be computationally intensive, especially when dealing with large-scale datasets. It is essential to consider how to make the model more scalable to meet real-time financial risk assessment demands. Secondly, our model relies on historical financial data for risk prediction, which may not fully capture sudden market fluctuations or unforeseen external events such as economic crises or global pandemics.

Looking ahead, our research holds significant implications for the financial industry. Accurate prediction of corporate financial risks is crucial for making informed investment decisions and ensuring market stability. Our model's success in this regard opens up opportunities for its application in various financial domains, including asset management, lending, and risk assessment. In future work, we will focus on refining the model to address its limitations, making it more robust and efficient. Firstly, further optimizing the ABC algorithm through techniques such as parallel computing and distributed computing can significantly enhance computational efficiency, making the model more scalable to meet real-time demands. Additionally, future research can explore the integration of real-time data sources, such as real-time market data and sentiment analysis of news, and the incorporation of external factors to bolster the model's adaptability to rapidly changing financial environments. This can be achieved by employing satellite models or implementing external event alert systems, as well as utilizing incremental learning approaches to continuously update the model.

In conclusion, our research represents a significant step in the field of corporate financial risk prediction. By combining the ABC-Attention-GRU model, we have developed a powerful tool poised to lead innovation in risk assessment practices within the financial industry. Despite the challenges, our work lays the foundation for future progress and underscores the importance of leveraging innovative approaches when addressing complex financial challenges.

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AVAILABILITY OF DATA AND MATERIALS

The data and materials used in this study are not currently available for public access. Interested parties may request access to the data by contacting the corresponding author.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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