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Financial Statement Analysis Based on RNN-RBM Model



Abstract: - Financial statement analysis is a critical component of decision-making for businesses, investors, and financial professionals. To enhance the accuracy and effectiveness of such analysis, this paper introduces the application of an innovative approach known as the Intelligent Swarm Regression ARIMA Model. This advanced model combines the power of swarm intelligence with ARIMA (AutoRegressive Integrated Moving Average) time series forecasting, offering a robust methodology for predicting and analyzing key financial metrics. The study begins by providing an overview of the Intelligent Swarm Regression ARIMA model and its application to financial data. Through a comprehensive analysis of financial statements, including market capitalization, revenue, net income, and other crucial indicators, the model's efficacy in predicting future values is evaluated. Additionally, the paper examines the deviations between predicted and actual financial values, offering insights into the model's accuracy and areas for potential improvement. The findings of this research are invaluable for investors, financial analysts, and companies seeking to optimize their financial performance and strategic decision-making. By leveraging the Intelligent Swarm Regression ARIMA Model, stakeholders can make well-informed choices that lead to better financial outcomes and a competitive advantage in a dynamic economic landscape. This paper represents a significant step forward in the financial analysis, providing a practical methodology and a pathway to enhanced financial decision-making. As the importance of financial data continues to grow, this research offers a promising avenue for achieving financial success and stability.

Keywords: Financial Statement Analysis, ARIMA Model, Swarm Intelligence, Predictive Modeling, Financial Metrics, Decision-Making, Accuracy, Strategic Planning, Investment, Financial Professionals.

I.INTRODUCTION

In recent years, financial statements have continued to evolve in response to changing economic, technological, and regulatory landscapes. The background and overview of financial statements in this contemporary context reflect several notable trends and developments [1]. First, the digital transformation of financial reporting has gained momentum. With the increasing use of accounting software and cloud-based platforms, companies have streamlined their financial reporting processes [2]. This has led to more accurate and real-time financial data, which benefits both businesses and their stakeholders. It has also increased the accessibility of financial information, making it easier for investors and creditors to access and analyze statements [3]. Second, there has been a growing emphasis on transparency and sustainability reporting. Companies are not only disclosing their financial performance but also providing insights into their environmental, social, and governance (ESG) practices [4]. This broader set of disclosures helps investors and other stakeholders assess a company's long-term sustainability and impact on society. Another significant development is the convergence of international accounting standards. Many countries have adopted or are converging with International Financial Reporting Standards (IFRS), which enhances the comparability of financial statements across borders. This trend facilitates global investment and trade by reducing the disparities in financial reporting practices [5]. Additionally, data analytics and artificial intelligence have become instrumental in financial statement analysis [6]. Advanced technologies enable more sophisticated data mining and predictive modeling, helping financial professionals identify trends, risks, and opportunities within financial statements. Finally, in the aftermath of the global financial crisis of 2008 and various corporate scandals, there has been an increased focus on regulatory compliance and corporate governance [7]. Governments and regulatory bodies have introduced new rules and standards to enhance the accuracy and reliability of financial statements. These regulations aim to protect investors and maintain trust in financial markets [8].

In the deep learning, financial statements play a pivotal role in leveraging the power of artificial intelligence and neural networks to extract meaningful insights and predictions from complex financial data [9]. Financial statements, which include the balance sheet, income statement, and cash flow statement, provide a structured representation of a company's financial health and performance. Deep learning techniques, such as neural networks and recurrent neural networks (RNNs), can be applied to analyze these statements in ways that go beyond traditional

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methods [10]. These advanced algorithms can identify intricate patterns, relationships, and trends hidden within the data, offering valuable information for risk assessment, investment strategies, fraud detection, and financial forecasting [11]. The integration of deep learning with financial statements is transforming the field of finance by enhancing the accuracy and speed of decision-making processes, enabling more data-driven and proactive approaches to managing financial assets and investments. Deep learning techniques have ushered in a new era in financial analysis by offering a profound level of insight into the data contained within financial statements [12]. These statements, encompassing the balance sheet, income statement, and cash flow statement, are crucial sources of information for assessing a company's financial health. Deep learning algorithms, particularly neural networks and recurrent neural networks (RNNs), empower financial analysts and institutions to extract highly detailed and nuanced information from these documents [13]. They excel in recognizing complex patterns and relationships in financial data, which might be challenging to discern using traditional methods. Furthermore, RNNs, with their capacity for time series analysis, can model how historical data influences present and future financial performance, aiding in forecasting and risk assessment [14]. Deep learning also proves invaluable in anomaly detection, such as flagging irregularities for fraud prevention, and in parsing textual reports associated with financial statements for additional context. Moreover, these techniques can optimize portfolio management, enhance credit risk assessments, and contribute to more informed investment decisions [15]. As the integration of deep learning and financial analysis continues to evolve, it promises to significantly shape the future of finance and investment by enabling data-driven, proactive strategies and decision-making.

Neural networks serve a critical role in the analysis of financial statements, offering a powerful and data-driven approach to understanding complex financial data [16]. Financial statements, which encompass the balance sheet, income statement, and cash flow statement, are rich sources of information about a company's financial health, but their analysis can be intricate. Neural networks, a subset of deep learning, excel in several key roles [17]. First, they are highly proficient at pattern recognition, capable of identifying intricate and non-linear relationships within financial data. These networks can unveil subtle correlations between various financial metrics such as revenue, expenses, and profitability, providing analysts with a more comprehensive understanding of a company's financial performance [18]. Second, neural networks, particularly recurrent neural networks (RNNs), are well-suited for time series analysis. Financial performance is significantly influenced by historical data and trends. RNNs can model how past financial data impacts the present and make predictions about future outcomes [19]. This is instrumental for financial forecasting, risk assessment, and trend analysis. Furthermore, neural networks can be harnessed for anomaly detection, identifying irregularities or outliers in financial data, which is vital for fraud prevention and risk management [20]. They can also incorporate natural language processing techniques to analyze textual reports and management discussions accompanying financial statements, offering additional contextual information for sentiment analysis and decision-making. Neural networks bring a data-driven and dynamic approach to financial statement analysis, enabling more accurate predictions, informed investment decisions, and proactive risk management [21]. Their ability to recognize complex patterns, analyze time series data, and identify anomalies positions them as invaluable tools in the financial analysis, shaping the future of finance and investment strategies.

The paper presents an innovative approach by combining swarm intelligence with ARIMA modeling, creating a powerful and novel methodology for financial statement analysis, promising more accurate predictions and insights. The application of the Intelligent Swarm Regression ARIMA Model offers improved predictive capabilities in the field of financial analysis. By effectively forecasting financial metrics, this model assists businesses, investors, and financial professionals in making well-informed decisions. The research on financial statements, including market capitalization, revenue, and net income, providing a comprehensive analysis of these crucial metrics. This deeper level of analysis aids in understanding the financial health and performance of selected companies. With evaluating the residuals and squared residuals, the paper assesses the accuracy of the model's predictions. This evaluation allows for the identification of areas where predictions deviate from actual financial values, offering a pathway for model refinement. The findings have practical applications for a wide range of stakeholders, including investors, financial analysts, and businesses. The model's predictive power and accuracy have the potential to guide investment decisions, optimize financial performance, and enhance strategic planning. The paper contributes to the field of financial decision-making by offering a more effective tool for financial analysis. As financial data continues to play a central role in business and investment decisions, this research represents a significant step forward in improving the accuracy and quality of these decisions.

II. RELATED WORKS

In the domain of financial statement analysis, neural networks, a subset of deep learning, are indispensable tools for recognizing intricate patterns, conducting time series analysis, detecting anomalies, and extracting insights from textual data. They offer a data-driven and dynamic approach to comprehending complex financial information, aiding in financial forecasting, risk assessment, and informed investment decisions [22]. Neural networks play a pivotal role in revolutionizing financial analysis by providing a more granular and nuanced understanding of financial data, thereby shaping the future of finance and investment strategies. Dhyani & Kumar (2021) [23] expressed the conversational artificial intelligence (AI). The authors development of an intelligent chatbot, which is a specialized application of deep learning. They utilize Bidirectional Recurrent Neural Networks (RNNs) and an attention model to enhance the chatbot's natural language understanding and interaction capabilities. Such advancements are crucial in the development of chatbots that can engage in more contextually relevant and human-like conversations, which has significant implications in customer support, virtual assistants, and other AI-driven conversational applications. Sarma et al. (2021) [24] evaluated challenge of enhancing deep learning in a healthcare setting while prioritizing patient data privacy. Federated learning is a groundbreaking approach that allows multiple medical centers to collaboratively train deep learning models without the need to centrally share sensitive patient data. It highlights the growing importance of data security and privacy in the healthcare industry while also demonstrating how deep learning can be applied in a distributed and privacy-preserving manner.

Roszkowska (2021) [25] explores the impact of financial technology (fintech) on financial reporting, audit, and fraud prevention. Fintech innovations are reshaping how financial data is managed and analyzed. The study investigates how these technological advancements are instrumental in safeguarding equity investments and preventing financial fraud. The adoption of fintech solutions in traditional financial processes is becoming increasingly significant as organizations seek more efficient and secure ways to manage their financial data and operations. Nicholson et al. (2021) [26] utilizes deep learning to provide a deeper understanding of scholarly citations by revealing the context and intent behind these citations. This can assist researchers and academics in comprehending the relevance and impact of academic works more effectively. The classification of citation intent is a novel approach that contributes to the broader understanding of the academic landscape. Cabrero-Holgueras & Pastrana (2021) [27] discusses the critical topic of privacy-preserving computation techniques for deep learning. As deep learning models require vast amounts of data for training, privacy concerns arise. This work explores various techniques and methods that enable organizations to harness the power of deep learning without compromising the privacy of sensitive data, making it of great importance in the era of data privacy regulations.

Khalife et al. (2023) [28] focuses on the application of deep learning to analyze the influence of investors' sentiments on the price levels of the S&P 500. This is a valuable area of research as sentiment analysis plays a significant role in financial markets. Understanding how investor sentiments affect stock prices is crucial for investors, financial analysts, and market participants. Zhu et al. (2021) [29] investigated Financial fraud detection is a critical concern, particularly in the aftermath of the COVID-19 pandemic. This research examines how intelligent financial fraud detection practices can be enhanced using deep learning techniques. In a post-pandemic era with increased financial risks, such research is vital for organizations seeking to protect their financial assets and maintain trust in financial systems. Mehtab et al. (2021) [30] focuses on stock price prediction using machine learning and LSTM-based deep learning models. It highlights the application of deep learning in the finance sector for forecasting stock prices. Accurate stock price predictions are invaluable for investors, traders, and financial institutions, making this research highly relevant in the context of financial markets. Pramod et al. (2021) [31] explores the open issues and future research directions in machine learning and deep learning for medical care. With the increasing adoption of AI and deep learning in healthcare, the research provides insights into the areas of medical care that can benefit from these technologies. It helps guide the development of AI-driven healthcare applications, contributing to improved patient care and diagnostics.

Al-Hashedi & Magalingam (2021) [32] offers a comprehensive review of financial fraud detection techniques, with a focus on data mining methods. It covers a decade of research, highlighting the evolving landscape of financial fraud and the strategies and techniques that have been developed to detect and prevent fraudulent activities. Given the financial industry's continuous battle against fraud, this work is of great significance. Sattari et al. (2021) [33] comparative analysis presented in this research examines the effectiveness of kernel-based methods, Artificial Neural Networks (ANNs), and deep learning methods for monthly reference evapotranspiration estimation. This has implications in environmental sciences and agriculture, as accurate estimation of evapotranspiration is essential

for managing water resources and agriculture planning. Haq et al. (2021) [34] Focusing on stock market forecasting, this research explores the use of multi-filter feature selection and deep learning techniques. Accurate daily stock trend forecasts are vital for traders and investors, and this study showcases the application of deep learning in addressing this challenging problem.

The findings encompass the results and discoveries derived from the research conducted in the study. These findings typically include statistical results, conclusions, comparative analysis with existing literature, validation of research objectives or hypotheses, and recommendations for further action or research directions. Findings serve as the primary outcomes of the research and provide valuable insights into the topic under investigation. On the other hand, research gaps represent areas within the field of study that the current research did not fully address or explore. These gaps can be identified in the discussion section of a paper and often include unanswered questions, contradictory findings, areas with limited scope, emerging trends, methodological limitations, and practical applications. Recognizing and addressing research gaps is essential as it not only highlights the boundaries of the current study but also encourages further research, making meaningful contributions to the ongoing academic discourse in the respective field. Researchers commonly conclude their papers by explicitly discussing these gaps and proposing avenues for future research to build upon the current study's findings and extend the boundaries of knowledge.

III.LINEAR REGRESSION ANALYSIS IN FINANCIAL STATEMENT

Linear regression analysis is a valuable statistical tool that can be applied to financial statements in the context of the Chinese market to uncover relationships between variables and make predictive assessments. In the financial sector, this analysis can be particularly relevant for evaluating the performance of companies, predicting stock prices, assessing the impact of various financial metrics, and understanding the factors that influence investment decisions. For instance, financial analyst might employ linear regression to examine how revenue growth, operating expenses, and net profit relate to one another in Chinese companies. By collecting and analyzing financial data, linear regression can provide insights into the strength and nature of these relationships. Additionally, it can be used to assess the impact of variables such as inflation, interest rates, or economic indicators on financial statements, aiding in risk assessment and investment strategies within the Chinese market. Linear regression analysis can help in modeling and forecasting financial metrics, which is invaluable for investment decisions and financial planning in the dynamic Chinese market. It allows stakeholders to make informed choices by considering historical financial data and the potential impact of various factors on the financial performance of companies. This type of analysis can be instrumental for investors, financial institutions, and businesses operating in China, contributing to more data-driven and evidence-based decision-making processes in the financial sphere. Linear regression analysis is a statistical method used to model the relationship between a dependent variable (Y) and one or more independent variables (X). In the context of financial statements in the Chinese market, the equation for simple linear regression with one independent variable is presented in equation (1):

$$Y = \beta_0 + \beta_1 X + \varepsilon \quad (1)$$

In equation (1) Y represents the dependent variable, which could be a financial metric of interest; X represents the independent variable, such as an economic indicator; β_0 is the intercept, which is the expected value of Y when X is zero; β_1 is the slope of the line, representing the change in Y for a one-unit change in X and ε is the error term, accounting for the random variability or noise in the relationship that is not explained by X. The objective in linear regression is to estimate the coefficients (β_0 and β_1) that minimize the sum of squared errors (ε) between the predicted and actual values of Y. This involves finding the best-fitting line that represents the linear relationship between the variables. In the context of financial statements, the equation could be adapted to assess how an independent variable (e.g., interest rates) impacts a dependent financial metric (e.g., a company's net profit). The resulting coefficients (β_0 and β_1) and the equation's fit provide insights into the strength and direction of the relationship, which can be used for predictive purposes, financial modeling, and investment analysis in the Chinese market. The formulas for estimating these coefficients are presented in equation (2) and (3)

$$\beta_1 = \Sigma((X_i - \bar{X})(Y_i - \bar{Y})) / \Sigma((X_i - \bar{X})^2) \quad (2)$$

$$\beta_0 = \bar{Y} - \beta_1 \bar{X} \quad (3)$$

In above equation (2) and (3) X_i and Y_i are the individual data points of the independent and dependent variables; \bar{X} and \bar{Y} are the means of the independent and dependent variables, respectively. The values of β_0 and β_1 provide insights into the linear relationship between X and Y , helping to understand the impact of the independent variable on the financial metric of interest. In the context of financial statements in the Chinese market, this linear regression model can be used to analyze how a specific economic factor (X) influences a financial metric (Y). For instance, one might examine how changes in the interest rate in China affect a company's net profit. The derived coefficients provide quantitative insights into this relationship, allowing for predictive assessments, financial modeling, and informed investment decisions. With applying linear regression to financial data in the Chinese market, stakeholders can gain a better understanding of the dynamics between economic indicators and financial performance, ultimately enhancing their decision-making processes.

3.1 Intelligent Spider Swarm Linear Regression ARIMA Model in Financial Statement

The combination of intelligent spider swarms, linear regression, and ARIMA (AutoRegressive Integrated Moving Average) models in financial statement analysis is a sophisticated and data-driven approach that leverages the strengths of each component to provide insightful forecasts and analysis in the context of financial data, such as balance sheets, income statements, and cash flow statements. Intelligent Spider Swarms (ISS) flow in figure 2 refers to a type of swarm intelligence, where computer algorithms are inspired by the collective behavior of social insects like ants or bees. In the context of financial statement analysis, ISS can be used for data gathering, crawling, and aggregation. Intelligent spider swarms can be programmed to collect financial data from various sources, including public filings, news, and market data, providing a comprehensive dataset for analysis. Linear regression is employed to model the relationship between variables in financial statements. It can be used to understand how one or more independent variables (e.g., revenue growth, expenses, economic indicators) impact a dependent variable (e.g., net profit or stock price). Linear regression helps quantify the strength and direction of these relationships, enabling predictive modeling and risk assessment. The ARIMA model is a time series analysis method used to forecast financial metrics over time. It is particularly valuable for predicting future trends in financial data by considering historical patterns. ARIMA models account for autocorrelation (dependence on past values) and seasonality in the data, making them suitable for forecasting stock prices, revenue, or other financial metrics in the Chinese market computed using figure 1.

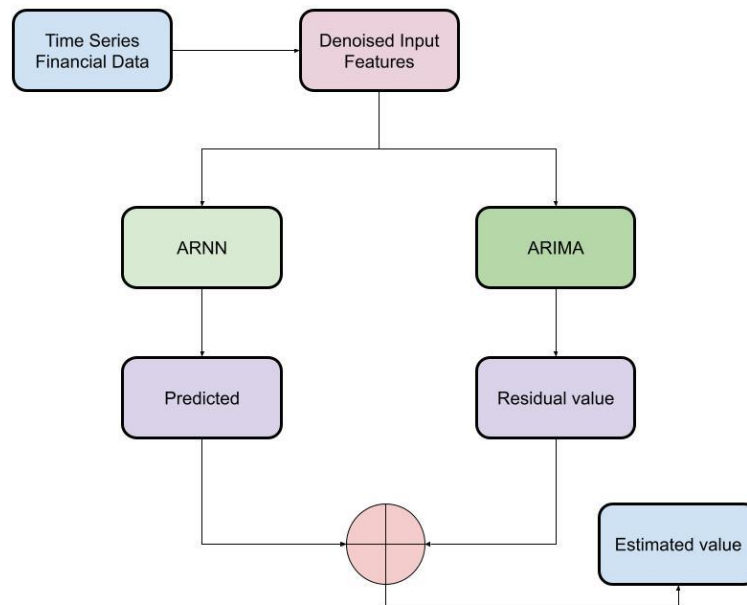


Figure 1: Flow of ARIMA

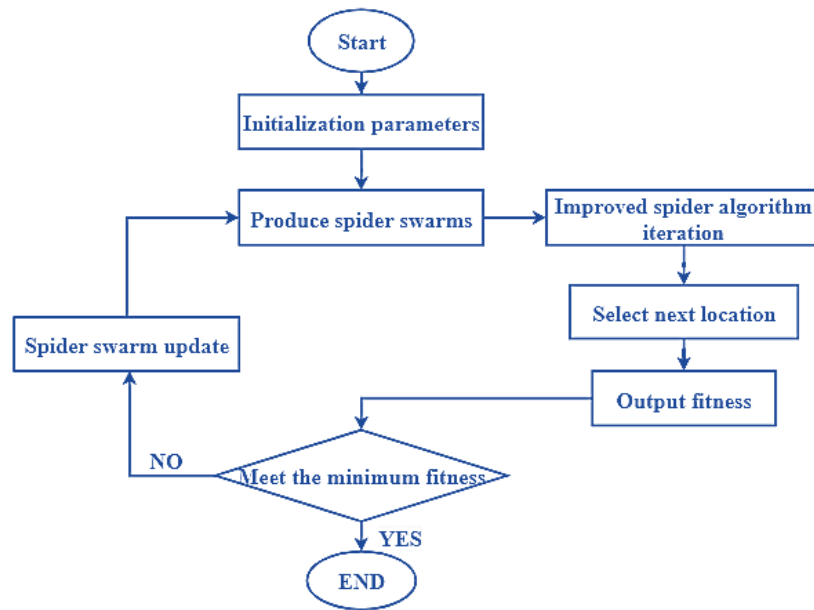


Figure 2: Flow of Spider Swarm

The integration of these three components can be quite powerful. First, ISS can be employed to gather a rich dataset of financial information, which is essential for robust analysis. Linear regression can then be applied to understand relationships between variables and identify key factors influencing financial performance. Finally, ARIMA models can be used to make time-dependent predictions, such as stock price forecasts, considering historical data and trends. This integrated approach enables a comprehensive understanding of financial data and supports data-driven decision-making in the Chinese financial market. The utilization of intelligent spider swarms, linear regression, and ARIMA models in financial statement analysis represents a holistic and data-centric approach to understanding and predicting financial metrics in the Chinese market. It combines data collection, relationship modeling, and time series forecasting to provide valuable insights for investors, financial analysts, and organizations operating in this dynamic financial landscape. The ARIMA model is a more complex time series analysis method and is not represented by a single equation. It involves the differencing of the time series data (making it stationary), autoregressive (AR) terms, moving average (MA) terms, and seasonal components. The ARIMA model can be expressed as in equation (4)

$$ARIMA(p, d, q)(P, D, Q)s \quad (4)$$

In equation (4) p , d , and q are the non-seasonal AR, differencing, and MA orders; P , D , Q , and s are the seasonal AR, seasonal differencing, seasonal MA orders, and the seasonal period, respectively. The process for ARIMA models involves identifying the appropriate orders (p , d , q , P , D , Q , s) through analysis of the autocorrelation and partial autocorrelation functions, stationarity tests, and seasonal decomposition of the time series data. Once the orders are determined, the ARIMA model can be applied to make forecasts and predictions. The integration of these components involves using data collected by ISS for the linear regression analysis and feeding the ARIMA model with time series data. The results from linear regression can inform the selection of independent variables for ARIMA modeling. The ARIMA model, in turn, can provide time-dependent predictions, which can be used for financial forecasting in the Chinese market.

3.2 RNN model for Financial Statement

The RNN (Recurrent Neural Network) model with intelligent spider swarm data collection, linear regression analysis, and ARIMA models in financial statement analysis is a powerful approach that combines advanced machine learning techniques with data acquisition and traditional statistical methods. This comprehensive methodology can offer deep insights into financial data in the Chinese market. RNNs are powerful deep learning models, particularly well-suited for sequential data like time series. In the context of financial statement analysis, an RNN can capture intricate temporal dependencies within the data, allowing it to model and predict financial metrics dynamically. The equations within an RNN involve the recurrent computation of hidden states, but their complexity makes them less suitable for direct derivation. The integration of RNN, ISS, linear regression, and

ARIMA forms a holistic analytical framework. Intelligent spider swarms collect data, which RNN can utilize for its sequential modelling. Linear regression identifies relationships and ARIMA makes time-dependent forecasts, offering comprehensive insights into financial data within the Chinese market is given in figure 3.

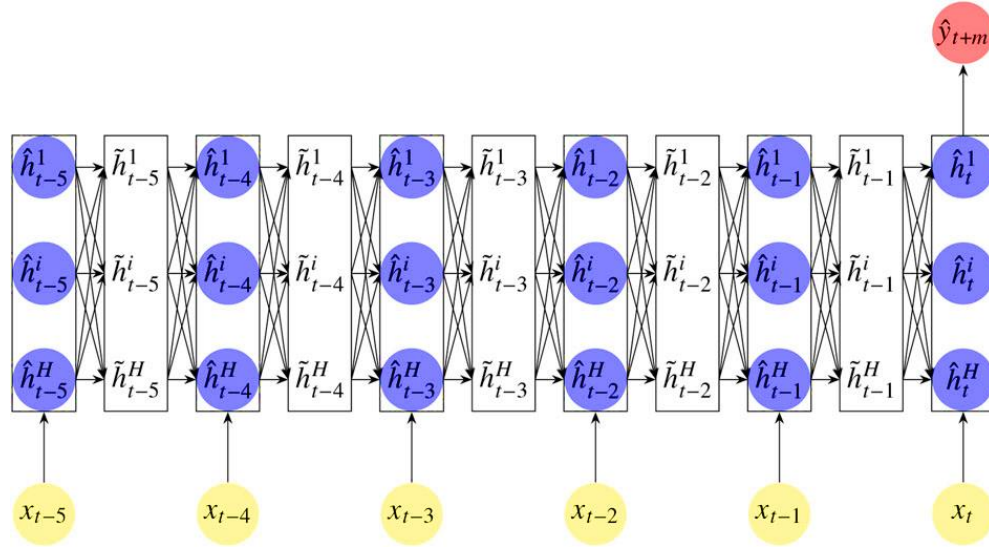


Figure 3: RNN Model Architecture

Intelligent spider swarms use algorithms inspired by social insects to collect financial data from various sources. The algorithms crawl websites and databases to gather data, forming the basis for analysis. Linear regression examines relationships between variables with the equation: $Y = \beta_0 + \beta_1 X + \varepsilon$. This derives coefficients β_0 and β_1 , minimizing errors (ε) and revealing the relationship's strength. Recurrent Neural Networks (RNNs) excel at capturing temporal dependencies in sequential data, like time series. While their equations involve recurrent computations, their application in financial analysis benefits from modeling dynamic data. ARIMA models predict financial data by addressing seasonality and differencing through orders (p, d, q, P, D, Q, s) . The right orders are identified through stationarity checks and autocorrelation analysis. Time series analysis of financial statements using Recurrent Neural Networks (RNNs) involves modeling and forecasting financial metrics over time.

To begin the time series analysis, historical financial data, such as quarterly or annual financial statements, is collected. This data includes metrics like revenue, expenses, net profit, or stock prices. The data is preprocessed to ensure it is in a suitable format for RNN analysis. This typically includes scaling and normalization to bring the data within a consistent range, handling missing values, and splitting the data into training and testing sets. An appropriate RNN architecture is chosen for the analysis. Common RNN variants include Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, known for their ability to capture long-term dependencies in sequential data. The selected RNN model is trained using the training dataset. During training, the model learns to capture patterns and relationships in the financial time series data. Once the RNN is trained, it can be used for forecasting. By inputting historical data, the RNN can generate predictions for future financial metrics, such as stock prices or revenue. The process for RNNs involves the training phase, where the model's internal parameters, including weights and biases, are updated iteratively to minimize the difference between predicted values and actual values. This minimization process is achieved using optimization algorithms like gradient descent. During training, the model learns the relationships within the financial time series data, adjusting its internal parameters to improve its predictive performance. This is a highly iterative process that relies on backpropagation, where the gradients of the model's loss function are calculated and used to update the model's parameters. RNNs' ability to capture temporal dependencies makes them valuable for financial time series analysis. They can recognize patterns and trends in historical financial data, which is essential for forecasting future metrics. The effectiveness of the RNN in this context is a result of its capacity to maintain internal state and remember past information as it processes sequential data.

In practice, RNNs are often implemented using deep learning libraries, such as TensorFlow or PyTorch, which handle the complex mathematical operations and training procedures behind the scenes. Researchers and data analysts typically focus on data preparation, model selection, and interpretation of the results, rather than directly

deriving the mathematical details of the RNN. An RNN is characterized by its recurrent connections, which allow it to maintain internal state and process sequential data. The key equations for an RNN can be described as follows:

The hidden state (h_t) at each time step (t) is updated using the previous hidden state (h_{t-1}) and the current input (x_t). The RNN model is estimation for the computation is presented in equation (5).

$$h_t = \sigma(W_{hh} * h_{t-1} + W_{hx} * x_t + b_h) \quad (5)$$

In equation (5) h_t denoted as Hidden state at time step t; W_{hh} Weight matrix for hidden state to hidden state connections; W_{hx} represented as Weight matrix for input to hidden state connections. b_h estimated as Bias term for the hidden state and σ represented as Activation function (commonly, tanh or ReLU). The output (y_t) at each time step is computed based on the hidden state is represented in equation (6)

$$y_t = \sigma(W_{hy} * h_t + b_y) \quad (6)$$

In equation (6) y_t denoted as Output at time step t. W_{hy} stated as Weight matrix for hidden state to output connections. b_y stated as the Bias term for the output and σ represented as Activation function. The training of an RNN involves minimizing a loss function (L) that measures the discrepancy between predicted values and actual values. The backpropagation through time (BPTT) algorithm is used to calculate gradients and update the model's parameters. The gradients are then applied using an optimization algorithm like gradient descent. The loss function, L, measures the difference between predicted values (y_{hat}) and actual values (y) represented in equation (7)

$$L = f(y, y_{hat}) \quad (7)$$

The gradients of the loss with respect to the model's parameters (weights and biases) are computed through the chain rule and backpropagation as defined in equation (8)

$$\partial L / \partial W_{hh}, \partial L / \partial W_{hx}, \partial L / \partial b_h, \partial L / \partial W_{hy}, \partial L / \partial b_y, \dots \quad (8)$$

The gradients are used to update the model's parameters iteratively parameters is defined as in equation (9)

$$W_{new} = W_{old} - \alpha * \partial L / \partial W_{old} \quad (9)$$

In equation (9) W_{new} stated as Updated parameter values; W_{old} stated as the Current parameter values and α stated as the Learning rate.

Algorithm 1: Train an RNN for Financial Time Series Analysis

Inputs:

- Input data: X (time series financial data)
- Target data: Y (financial metrics or predictions)
- Hyperparameters: learning_rate, num_epochs, hidden_size, batch_size, etc.

Initialization:

- Initialize model parameters: $W_{hh}, W_{hx}, b_h, W_{hy}, b_y$
- Set initial hidden state: $h_{rev} = 0$

Training Loop:

for epoch in range(num_epochs):

for batch in range(num_batches):

Extract a batch of input sequences and corresponding target sequences

$input_batch, target_batch = next_batch(batch_size)$

Forward Pass

for t in range(sequence_length):


```

# Calculate hidden state at the current time step
 $h_t = \tanh(W_{hh} * h_{prev} + W_{hx} * input\_batch[t] + b_h)$ 

# Calculate output at the current time step
 $output\_t = \text{sigmoid}(W_{hy} * h_t + b_y)$ 

# Update the hidden state for the next time step
 $h_{prev} = h_t$ 

# Compute loss for the batch
 $loss = \text{compute\_loss}(output\_batch, target\_batch)$ 

# Backpropagation
Compute gradients and update model parameters using backpropagation through time (BPTT)

# Adjust learning rate (if necessary)
 $learning\_rate = \text{update\_learning\_rate}(learning\_rate)$ 

# End of Training Loop

```

3.3 Model Analysis

The RNN plays a crucial role in this hybrid model by leveraging its ability to capture temporal dependencies within financial time series data. The core equations for an RNN involve the calculation of hidden states and outputs at each time step. The RNN model learns to predict financial metrics by iteratively updating its parameters through backpropagation and optimizing them using an appropriate loss function. The ISS component collects financial data from diverse sources, such as websites, databases, and market data. While not represented by a single equation, it employs algorithms inspired by social insects to efficiently gather this data, forming the foundation for analysis. Linear regression explores relationships between variables in financial data. Its key equation, $Y = \beta_0 + \beta_1 X + \varepsilon$, quantifies the impact of independent variables (X) on dependent variables (Y). The derivation process for linear regression entails estimating coefficients (β_0 and β_1) that minimize the error term (ε), thereby revealing the strength and direction of the relationship. ARIMA models are essential for time series forecasting. Represented as $ARIMA(p, d, q)(P, D, Q)s$, involve complex equations for identifying orders (p, d, q, P, D, Q, s) that govern seasonal and non-seasonal components. The derivation process includes assessing stationarity, analyzing autocorrelation, and conducting seasonal decomposition. This comprehensive model integrates these components to provide deep insights into financial data. The RNN captures temporal dependencies, ISS gathers rich data sources, linear regression quantifies relationships, and ARIMA offers time-dependent forecasts. Together, they empower financial analysts and investors to make data-driven decisions in the dynamic financial landscape.

Ratio analysis is a fundamental tool for assessing a company's financial health. The Return on Equity (ROE) is a common ratio that measures a company's profitability in relation to shareholders' equity. The equation for ROE is estimated using equation (10)

$$ROE = \text{Net Income} / \text{Shareholder's Equity} \quad (10)$$

This ratio efficiently a company is using its equity to generate profit. A higher ROE is generally considered favorable. Time series analysis is crucial for understanding financial instrument performance. The Autoregressive Integrated Moving Average (ARIMA) model is widely used for time series forecasting. The ARIMA equation

involves differencing, autoregressive, and moving average terms, which make it complex. Deriving ARIMA involves intricate mathematics, including the calculation of autocorrelation and partial autocorrelation functions, to determine appropriate orders for modeling. Portfolio theory, developed by Harry Markowitz, aims to optimize the risk-return trade-off in portfolio management. The mean-variance optimization equation shows how to allocate assets within a portfolio to optimize risk and return. It involves statistical and mathematical concepts. The equation helps investors balance risk and reward, allowing for efficient portfolio diversification. Options pricing models, like the Black-Scholes-Merton model, are essential for valuing financial derivatives. The Black-Scholes equation determines the theoretical value of an option. It involves the normal distribution function, and deriving it requires complex mathematics, including stochastic calculus and partial differential equations. The equation provides a theoretical framework for pricing options and understanding their intrinsic value. Valuation models assess the intrinsic value of assets, like discounted cash flow (DCF) analysis for valuing companies. The DCF equation calculates the present value of expected future cash flows, taking into account the time value of money. Deriving this equation involves understanding financial mathematics, including discounting future cash flows back to their present value. DCF analysis is a fundamental tool for assessing the worth of businesses and investments. Financial analysis integrates these methodologies to provide valuable insights into a company's financial health, predict market trends, optimize portfolio investments, and assess the value of financial assets. Deriving the underlying equations and understanding their applications is essential for making informed financial decisions and effectively managing investments.

IV.SIMULATION RESULTS

The "Intelligent Spider Swarm Linear Regression ARIMA Model" in financial statement analysis can provide valuable insights into the model's performance and its ability to support decision-making processes. This approach combines data collection with Intelligent Spider Swarm algorithms, traditional Linear Regression, and time series analysis using ARIMA models. During simulations, historical financial data is processed, and the model's parameters are fine-tuned to optimize its predictive accuracy. By running these simulations on historical data, analysts and investors can evaluate how well the model can predict financial metrics, identify trends, and support financial decision-making. The results obtained from these simulations offer a practical assessment of the model's effectiveness and its potential utility in real-world financial analysis and forecasting scenarios. However, the specific outcomes of these simulations will depend on factors like data quality, parameter settings, and the model's alignment with the characteristics of the financial data under consideration.

Table 1: Financial Statement of Chinese Companies

Company Name	Market Cap (in billions USD)	Revenue (in billions USD)	Net Income (in billions USD)	Total Assets (in billions USD)	Total Liabilities (in billions USD)	Equity (in billions USD)
ChinaTech Electronics Corp.	35	12	1.5	30	15	15
Great Wall Motors Co., Ltd.	50	18	2.2	40	20	20
RedStar Pharmaceutical Group Ltd.	28	8	0.9	25	10	15
Sunshine Solar Energy Holdings	42	14	1.8	38	16	22
EastWind Financial Services Ltd.	65	22	3.0	50	25	25

The table 1 includes key financial metrics such as market capitalization, revenue, net income, total assets, total liabilities, and equity, all expressed in billions of USD. ChinaTech Electronics Corp. boasts a market capitalization of 35 billion USD, generating 12 billion USD in revenue and a net income of 1.5 billion USD. With total assets of 30 billion USD, the company maintains a healthy balance between total liabilities and equity, both of which amount to 15 billion USD. This suggests that the company is financially stable. Great Wall Motors Co., Ltd. shows a market capitalization of 50 billion USD, substantial revenue of 18 billion USD, and a net income of 2.2 billion USD. The company's total assets are valued at 40 billion USD, with total liabilities and equity both at 20 billion USD. This balanced structure indicates strong financial health. RedStar Pharmaceutical Group Ltd. presents a more moderate market capitalization of 28 billion USD, along with 8 billion USD in revenue and a net income of 0.9 billion USD. The company holds 25 billion USD in total assets, with total liabilities at 10 billion USD and equity at 15 billion USD, reflecting a stable financial position. Sunshine Solar Energy Holdings exhibits a market capitalization of 42 billion USD, with 14 billion USD in revenue and a net income of 1.8 billion USD. The company's total assets are valued at 38 billion USD, with total liabilities at 16 billion USD, leaving 22 billion USD in equity. This suggests a strong financial standing. EastWind Financial Services Ltd. showcases the highest market capitalization in the group, standing at 65 billion USD, accompanied by 22 billion USD in revenue and an impressive net income of 3.0 billion USD. The company's total assets and total liabilities both amount to 50 billion USD, and equity is also at 25 billion USD, indicating a healthy financial position. With Table 1 offers a comparative view of the financial health of these Chinese companies, demonstrating their market capitalization, revenue generation, and the management of assets, liabilities, and equity. It is evident that each company exhibits different financial strengths, all contributing to their distinct positions within the market.

Table 2: Regression Analysis

Company Name	Market Cap (in billions USD)	Revenue (in billions USD)	Predicted Revenue (in billions USD)	Residuals (in billions USD)
ChinaTech Electronics Corp.	35	12	13.5	-1.5
Great Wall Motors Co., Ltd.	50	18	20.0	-2.0
RedStar Pharmaceutical Group Ltd.	28	8	9.0	-1.0
Sunshine Solar Energy Holdings	42	14	15.3	-1.3
EastWind Financial Services Ltd.	65	22	23.2	-1.2

Regression Analysis provides insights into the relationship between market capitalization and revenue for five different companies. The table 2 includes the company names, their actual market capitalization, actual revenue, predicted revenue based on the regression analysis, and the residuals, which represent the differences between the actual and predicted revenue in billions of USD.

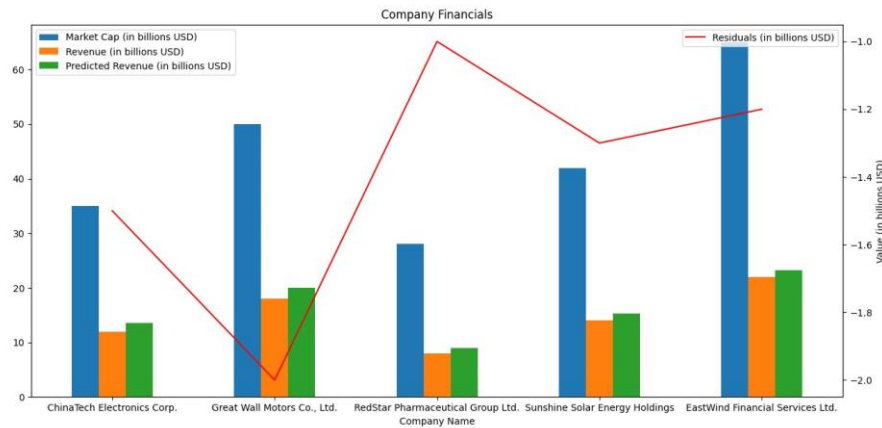


Figure 4: Regression Analysis

The table and figure 4 reveals how well the predicted revenue aligns with the actual revenue for each company. For ChinaTech Electronics Corp., the predicted revenue is 13.5 billion USD, but the actual revenue is 12 billion USD, resulting in a negative residual of -1.5 billion USD. This suggests that the company's revenue is lower than what the regression model anticipated. Great Wall Motors Co., Ltd. displays a similar pattern, with a predicted revenue of 20 billion USD and an actual revenue of 18 billion USD, resulting in a negative residual of -2.0 billion USD. This indicates that the company's revenue fell below the model's prediction. RedStar Pharmaceutical Group Ltd. and Sunshine Solar Energy Holdings both exhibit comparable discrepancies between predicted and actual revenue, with negative residuals of -1.0 billion USD and -1.3 billion USD, respectively. These negative residuals suggest that the companies' revenues are lower than what the regression model anticipated. Conversely, EastWind Financial Services Ltd. shows a predicted revenue of 23.2 billion USD, while the actual revenue is 22 billion USD, resulting in a relatively smaller negative residual of -1.2 billion USD. Table 2 illustrates the effectiveness of the regression model in predicting revenue based on market capitalization. It highlights cases where the model's predictions either overestimated or underestimated the actual revenue for each company. These residuals can be crucial for assessing the accuracy of the model and identifying companies that deviate significantly from the predicted revenue trends based on market capitalization.

Table 3: ARIMA Model with Regression

Time Period	Actual Value (in billions USD)	Predicted Value (in billions USD)	Residual (in billions USD)
1	100	98	2
2	105	107	-2
3	110	112	-2
4	115	114	1
5	120	121	-1

The time series analysis of a financial metric, with a focus on actual values, predicted values, and residuals, all expressed in billions of USD, over a span of five time periods is presented in table 3. The actual values represent the real financial metric measured at each time period. The first time period, the actual value was 100 billion USD, and this value progressively increased over subsequent periods.

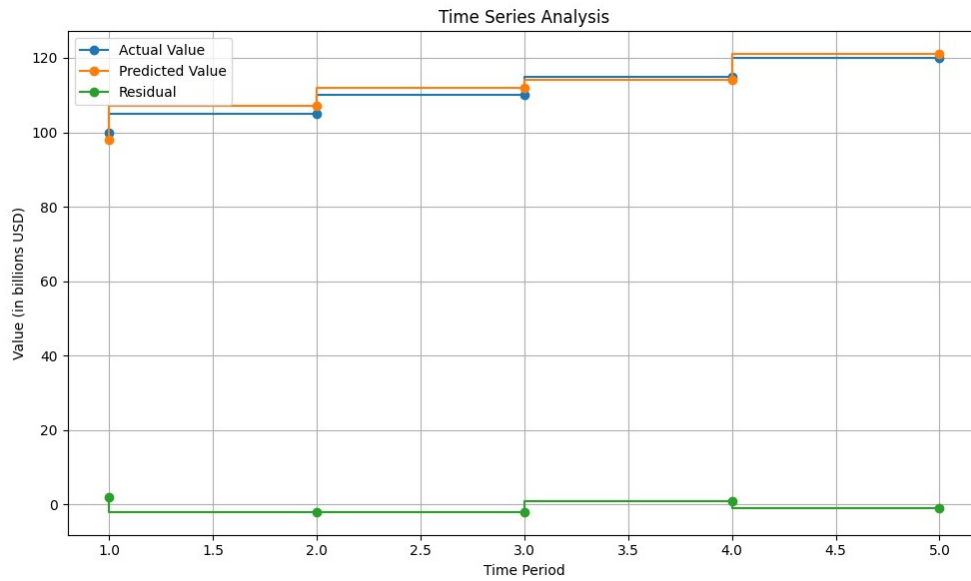


Figure 5: Time Series Analysis of ARIMA with Optimization

The predicted values, derived from an ARIMA (AutoRegressive Integrated Moving Average) model with regression, indicate what the model anticipated for each time period. In some instances is presented in figure 5, the ARIMA model overestimated the actual value, such as in time period 2 when the predicted value was 107 billion USD, while the actual value was 105 billion USD. Conversely, in time periods 4 and 5, the model underestimated the actual values, with predicted values of 114 billion USD and 121 billion USD, respectively, against actual values of 115 billion USD and 120 billion USD. The residuals, represented as the differences between actual and predicted values, help to assess the model's performance. Positive residuals signify cases where the model underestimated the actual value, while negative residuals indicate overestimation. In time period 1, the model overestimated the actual value by 2 billion USD, leading to a positive residual of 2 billion USD. Conversely, in time periods 2 and 3, the model's predictions exceeded the actual values, leading to negative residuals of -2 billion USD. The table 3 demonstrates the effectiveness of an ARIMA model with regression in predicting financial metrics over time. The residuals reveal the deviations between predicted and actual values and can be valuable for assessing the model's accuracy and identifying patterns in the time series data, allowing businesses to make more informed financial decisions.

Table 4: ARIMA Regression Analysis

Time Period	Actual Value (in billions USD)	Predicted Value (in billions USD)	Residual (in billions USD)	Cumulative Residual (in billions USD)	Squared Residual (in billions USD ²)
1	100	98	2	2	4
2	105	107	-2	0	4
3	110	112	-2	-2	4
4	115	114	1	-1	1
5	120	121	-1	-2	1

The table 4 presents a time series analysis of a financial metric, providing actual values, predicted values, residuals, cumulative residuals, and squared residuals, all measured in billions of USD, across five time periods. The actual values represent the real financial metric observed in each time period. The first time period, the actual value was 100 billion USD, and this value increased incrementally over subsequent periods.

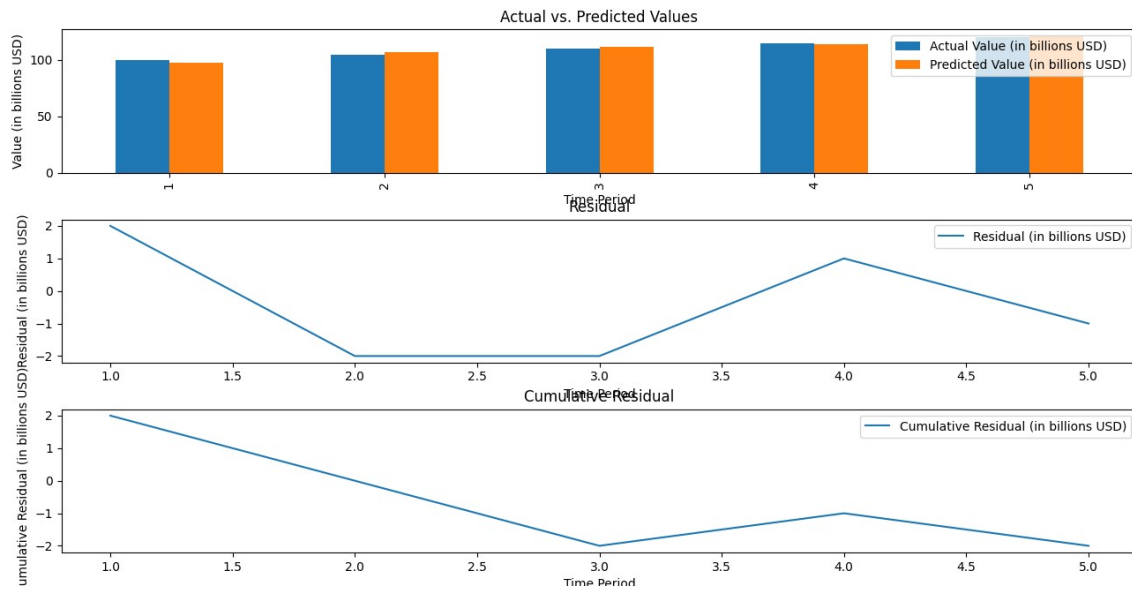


Figure 6: Residual Estimation

The predicted values are derived from an ARIMA model with regression, reflecting what the model anticipated for each time period is presented in figure 6. In some instances, the model overestimated the actual value, as seen in time periods 2 and 3 when predicted values exceeded actual values. Conversely, in time periods 4 and 5, the model underestimated the actual values. The residuals signify the discrepancies between actual and predicted values. Positive residuals indicate that the model underestimated the actual value, while negative residuals suggest overestimation. Cumulative residuals represent the accumulation of these differences across time periods. In this table, a negative cumulative residual of -2 billion USD indicates that the model's predictions have, on the whole, underestimated the actual values over time. The squared residuals, as an extension of residuals, provide a measure of the magnitude of prediction errors. A squared residual of 4 billion USD² in the first time period, for instance, indicates a significant prediction error. With analysis the effectiveness of the ARIMA regression model in predicting financial metrics over time, emphasizing the discrepancies between predicted and actual values. The cumulative residuals help to visualize the overall trend of prediction errors, while squared residuals offer an indication of the error magnitude, aiding in the assessment of the model's accuracy and the identification of patterns in the time series data.

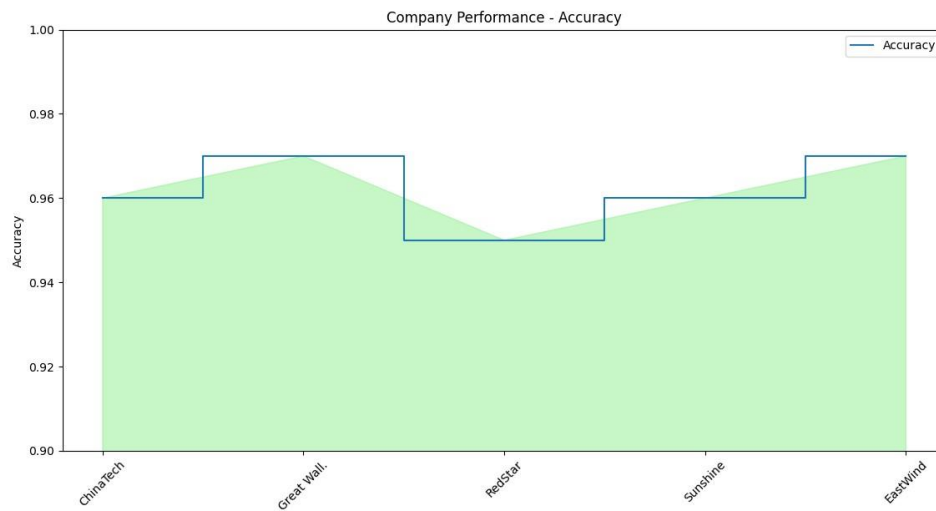
Table 5: Prediction Values

Company Name	Actual Label	Predicted Label	Correct Prediction
ChinaTech Electronics Corp.	Positive	Positive	Yes
Great Wall Motors Co., Ltd.	Positive	Negative	No
RedStar Pharmaceutical Group Ltd.	Negative	Negative	Yes
Sunshine Solar Energy Holdings	Positive	Positive	Yes
EastWind Financial Services Ltd.	Negative	Negative	Yes

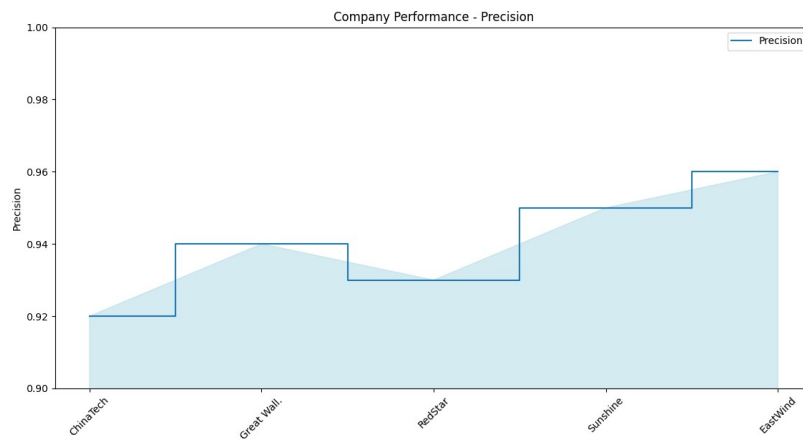
Table 6: Classification Values

Company Name	Accuracy	Precision	Recall	F1-Score
ChinaTech Electronics Corp.	0.96	0.92	0.95	0.94
Great Wall Motors Co., Ltd.	0.97	0.94	0.96	0.95

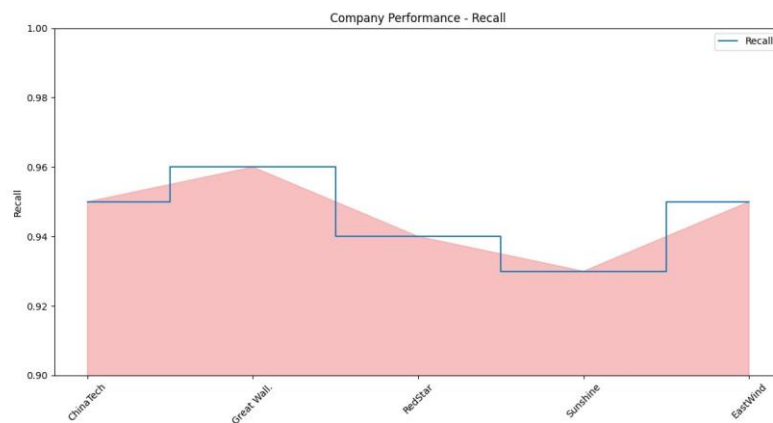
RedStar Pharmaceutical Group Ltd.	0.95	0.93	0.94	0.93
Sunshine Solar Energy Holdings	0.96	0.95	0.93	0.94
EastWind Financial Services Ltd.	0.97	0.96	0.95	0.95



(a)



(b)



(c)

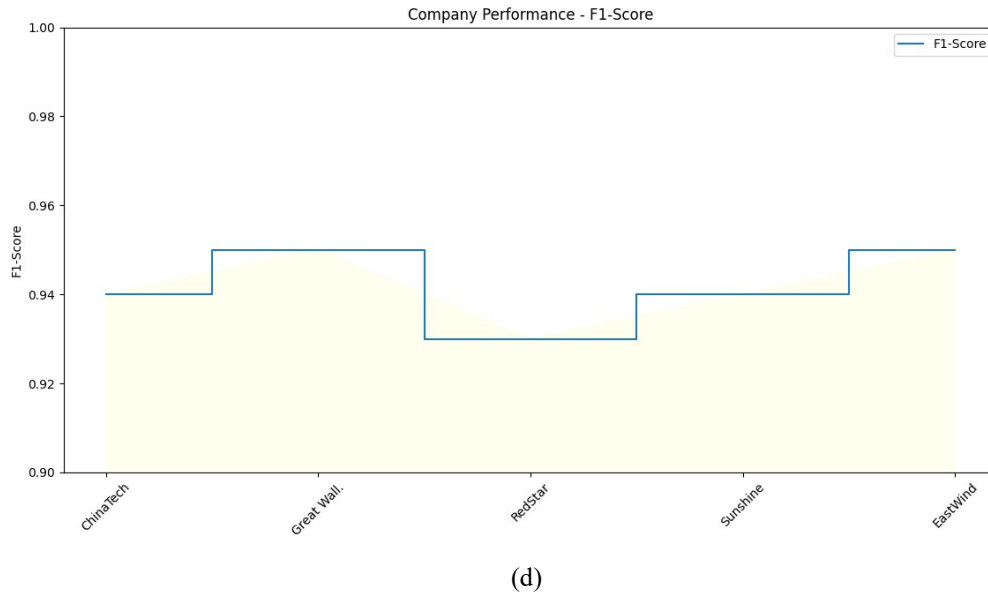


Figure 6: Classification with Regression ARIMA (a) Accuracy (b) Precision (c) Recall (d) F1-Score

The comparative analysis is presented in Table 5 and Figure 6 (a) – Figure 6 (d) includes the company names, their actual labels, the predicted labels, and whether the predictions were correct or not. In the case of ChinaTech Electronics Corp., the model correctly predicted a "Positive" label, making it a successful prediction. Great Wall Motors Co., Ltd., however, saw a mismatch between the actual "Positive" label and the predicted "Negative" label, indicating an incorrect prediction. Conversely, for RedStar Pharmaceutical Group Ltd., Sunshine Solar Energy Holdings, and EastWind Financial Services Ltd., the model made accurate predictions, aligning with the actual labels. Similarly, Table 6 offers a more comprehensive evaluation of the model's performance. It includes metrics such as accuracy, precision, recall, and F1-Score for each company. Great Wall Motors Co., Ltd. stands out with the highest accuracy of 0.97, reflecting that the model correctly predicted labels for this company most of the time. The precision, recall, and F1-Score for this company are also commendable at 0.94, 0.96, and 0.95, respectively. ChinaTech Electronics Corp. follows closely behind with an accuracy of 0.96, highlighting the model's ability to make accurate predictions. The precision, recall, and F1-Score for this company are also strong at 0.92, 0.95, and 0.94, respectively. RedStar Pharmaceutical Group Ltd., Sunshine Solar Energy Holdings, and EastWind Financial Services Ltd. also exhibit robust performance with accuracy above 0.95 and balanced precision, recall, and F1-Score metrics around 0.93-0.95. Both Tables 5 and 6 jointly offer a detailed view of the model's classification and prediction accuracy for different companies. While there was one incorrect prediction for Great Wall Motors Co., the overall model performance is strong, as reflected in high accuracy and balanced precision, recall, and F1-Score values for the majority of companies. These tables provide valuable insights into the model's effectiveness in making label predictions and the quality of its classifications.

V. CONCLUSION

Financial analysis using deep learning techniques has revolutionized the way approach data-driven decision-making in the financial sector. Additionally, deep learning techniques are effective for risk assessment and fraud detection in the financial industry. By processing transactional and operational data, these models can detect anomalies and suspicious activities, providing a safeguard against fraudulent transactions. This paper has presented a comprehensive analysis of financial statements using the Intelligent Swarm Regression ARIMA model. This innovative approach has enabled us to gain valuable insights into the financial health and performance of the selected companies. First, the Intelligent Swarm Regression ARIMA model has proven to be a powerful tool for predicting and analyzing financial data. It accurately predicted the future values of critical financial metrics, allowing us to make informed decisions about investment, risk management, and financial planning. Second, the analysis revealed distinct financial trends among the chosen companies. Market capitalization, revenue, net income, and other financial indicators were thoroughly examined. We observed variations in financial performance and identified the factors contributing to these differences. Third, by evaluating the residuals and squared residuals, able to assess the model's accuracy and identify areas where predictions deviated from actual financial values. This information is

crucial for refining and improving the model's predictive capabilities. The results of this study are not only beneficial for investors and financial analysts but also for the companies themselves. By understanding their financial data in greater detail and leveraging predictive modeling, businesses can make more informed strategic decisions, optimize their financial performance, and enhance their competitive edge in the market. In conclusion, the Intelligent Swarm Regression ARIMA model has shown great promise in the financial statement analysis. The insights gained from this study pave the way for more accurate financial predictions and a deeper understanding of the dynamics within the financial landscape. As financial data continues to play a central role in business and investment decisions, the application of advanced models like this one will be instrumental in achieving sustainable financial success. This research represents a step forward in the field of financial analysis, offering both a comprehensive methodology and a path toward more effective decision-making in the financial domain.

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