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ORIGINAL

Financial Risk Prediction for Agricultural Enterprises Using Intelligent Modeling and Dynamic State Analysis

Predicción del riesgo financiero para empresas agrícolas mediante modelos inteligentes y análisis dinámico de estado

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ABSTRACT

Agricultural enterprises have financial uncertainties due to market volatility, climate disruptions, and changes in policies; therefore, farming operations must use timely and accurate forecasts, as they are particularly vulnerable to external economic shocks and environmental variability. Standard forecasting methods usually cannot capture nonlinear dependencies and dynamic shifts in risk profiles; therefore, there is a need to consider intelligent, adaptive systems. Research proposes a novel financial risk prediction model using the Sooty Tern Optimization Algorithm Attention-Based Long Short-Term Memory (STOA-Att-LSTM). Financial risk data were collected, which included agricultural enterprise financial records, national weather databases, and commodity market indices. To ensure data integrity and modelling efficiency, two essential pre-processing techniques were employed. Handling missing values was performed using linear interpolation to reconstruct incomplete sequences, particularly in time-series financial and climatic data, to standardize variables, facilitating efficient model training and convergence. The STOA algorithm was used to optimize the hyper-parameters of the Att-LSTM model, enhancing its generalization and predictive accuracy. The attention mechanism enabled the model to dynamically focus on critical time-dependent features influencing financial risk. Dynamic state analysis further strengthened the framework by capturing temporal shifts in enterprise conditions. Model evaluation using Python-based implementation of error metrics and classification accuracy (0,9899) showed better results compared to traditional and baseline deep learning (DL) models. The proposed framework offers a robust, adaptive tool for proactive financial risk assessment in agricultural enterprises, supporting sustainable decision-making in uncertain environments.

Keywords: Financial risk Prediction; Deep Learning (DL); Sooty Tern Optimization Algorithm Attention-Based Long Short-Term Memory (STOA-Att-LSTM); Agricultural Enterprises; Climate Disruptions.

RESUMEN

Las empresas agrícolas se enfrentan a incertidumbres financieras debido a la volatilidad del mercado, las perturbaciones climáticas y los cambios en las políticas; por lo tanto, las operaciones agrícolas deben utilizar previsiones oportunas y precisas, ya que son especialmente vulnerables a las crisis económicas externas y a la variabilidad medioambiental. Los métodos de previsión estándar no suelen poder captar las dependencias no lineales y los cambios dinámicos en los perfiles de riesgo; por lo tanto, es necesario considerar sistemas inteligentes y adaptables. La investigación propone un novedoso modelo de predicción del riesgo financiero que utiliza el algoritmo de optimización Sooty Tern Optimization Algorithm Attention-Based Long Short-Term Memory (STOA-Att-LSTM). Se recopilaron datos sobre el riesgo financiero, que incluían registros financieros de empresas agrícolas, bases de datos meteorológicas nacionales e índices del mercado de materias primas. Para garantizar la integridad de los datos y la eficiencia de la modelización, se emplearon dos técnicas de preprocesamiento esenciales. El tratamiento de los valores perdidos se realizó mediante interpolación lineal para reconstruir secuencias incompletas, en particular en datos financieros y climáticos de series temporales, con el fin de estandarizar las variables y facilitar el entrenamiento y la convergencia eficientes del modelo. Se utilizó el algoritmo STOA para optimizar los hiperparámetros del modelo Att-LSTM, mejorando su generalización y precisión predictiva. El mecanismo de atención permitió al modelo centrarse dinámicamente en las características críticas dependientes del tiempo que influyen en el riesgo financiero. El análisis dinámico del estado reforzó aún más el marco al captar los cambios temporales en las condiciones de las empresas. La evaluación del modelo utilizando la implementación basada en Python de métricas de error y precisión de clasificación (0,9899) mostró mejores resultados en comparación con los modelos tradicionales y de referencia de aprendizaje profundo (DL). El marco propuesto ofrece una herramienta robusta y adaptable para la evaluación proactiva del riesgo financiero en las empresas agrícolas, lo que favorece la toma de decisiones sostenibles en entornos inciertos.

Palabras clave: Predicción del Riesgo Financiero; Aprendizaje Profundo (DL); Algoritmo de Optimización Sooty Tern; Memoria a Corto y Largo Plazo Basada en la Atención (STOA-Att-LSTM); Empresas Agrícolas, Perturbaciones Climáticas.

INTRODUCTION

The development of rural financial systems highlights the growing importance of family farms in enhancing farming productivity. Family farms focus on the maximum use of land and labor, optimizing to overcome inefficiencies caused by fragmented farming, and encouraging the use of new technology in farming. Growth facilitates improved resource allocation, national economic growth and global competitiveness in farm products.[1] However, agriculture continues to be susceptible to financial hazards through market volatility, increased input prices, and lack of access to finance. In some countries, risks are heightened by antiquated infrastructure, fragmented land ownership, and reduced financial systems, declining economic stability, and long-term growth.[2]

Traditional financial modelling techniques applied to agricultural businesses tend to be static and linear. Such frameworks do not incorporate the nonlinear dynamics and dynamic factors that influence agricultural finance. They do not allow flexibility to account for factors such as volatility in commodity prices, climatic changes, and supply chain difficulties, making them ineffective for assessing financial risks and supporting an effective decision-making process.[3] Enterprise Risk Management (ERM) systems show limitations in dynamic and complex sectors such as agriculture, current models tend to be inflexible and sector specific. Furthermore, evidence shows there are not enough effective technologies to map and address supply chain and financial risks. Agricultural businesses need intelligent, data-based ways to continuously scan the organization's environment for changing risk patterns to create more resilience.[4] Conventional farm management practices of mono-cropping and chemical pesticide use have led to issues including soil erosion and pest resistance, as well as decreased climate resilience.[5]

The Graph Neural Network (GNN) framework aimed to enhance management efficiency and competitiveness of agricultural input enterprises through cost analysis and financial risk warning.[6] Integrated Bayesian techniques identified key financial risk factors, though generalizability across varying enterprise scales and financial environments remained a limitation. The intelligent financial service framework incorporated DL and edge computing to maximize money distribution in rural areas.[7] Cooperatives for agriculture made implementation easier. The uniform impact was reduced by societal instability and unequal economic distribution. Practical learning, helping rural economic growth, and advancing the larger objectives of rural rejuvenation, validated resource optimization.

The theoretical framework focused on pricing trends for garlic and pork. It included policy-driven economic factors, utilized statistical models, and NN.[8,9,10] Accuracy was hampered by traditional predicting techniques. By incorporating data economics and technological advancements into the analysis of agricultural price trends, the suggested hybrid model improved the dependability of short-term predictions. The framework applied a convolutional NN to aerial imagery for forecasting wheat futures prices 20 days ahead.[9,11,12] It generated trading recommendations using cloud cover as a yield proxy. The model initially produced positive alpha; performance declined when data accessibility increased and market strategies became saturated. The substantial financial risks associated with agricultural enterprises were addressed under the corporate social responsibility framework to enhance sustainability and food security, especially during the COVID-19 epidemic.[10,13,14] There was no quantitative support for it using entrepreneurial risk theory. The financial risk management and sustainable agriculture from both Russia and other countries, the results highlighted the importance of Corporate Social Responsibility (CSR).[15,16,17] To estimate common factors, the dynamic factor model was used, influencing target topics and developing a sentiment index reflecting macroeconomic conditions.[11,18,19,20] It applied an improved agricultural economic risk-mining algorithm but lacked broad validation. Results demonstrated effective forecasting using data mining in agricultural economic risk assessment.

The research aims to build a smart model for evaluating financial risks in farming enterprises using the convergence of DL and metaheuristic optimization methods.[21,22,23] The proposed STOA-Att-LSTM, uses time-based market, environmental, and financial data to find dynamic relationships and non-linear interdependency between the items. The STOA method is used for hyper-parameter optimization, enhancing the learning capacity of the Att-LSTM model. The framework can provide timely and accurate risk classification, reducing uncertainties related to climate variability, market forces, and economic shocks, underpinning data-centric and sustainable agriculture decision-making.[24]

Paper Organizations

The remaining sections are structured as follows: The background information and research are presented in section 1. The methodology, including data and model structure, is explained in section 2. Results and comparisons are reported in section 3. Section 4 concludes the research with significant findings and recommendations for future studies in agricultural financial risk forecasting.

METHOD

The section begins by collecting a public agricultural financial risk dataset. Pre-processing involves linear interpolation by handling missing values. STOA optimizes hyper-parameters of an Att-LSTM, which models temporal dependencies and highlights key risk factors for accurate, adaptive financial risk prediction in agricultural enterprises. The proposed flow is depicted in figure 1.

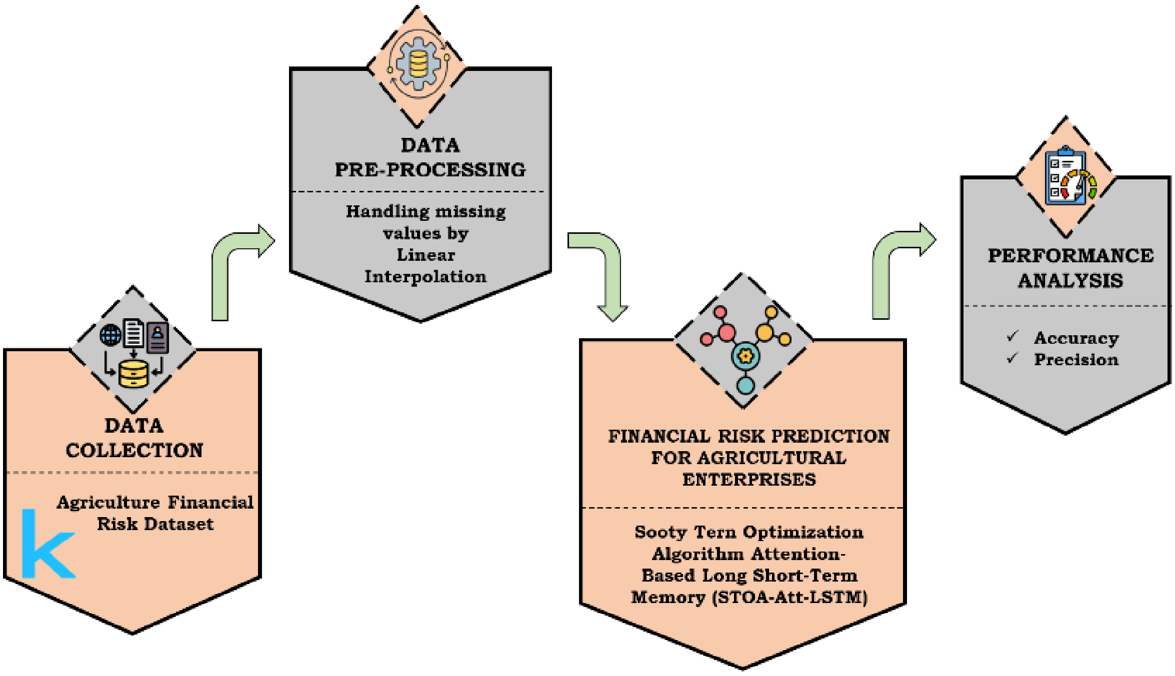

Figure 1. Overview of the Proposed Model

Datasets

The data was obtained from the publicly available Agriculture Financial Risk Dataset at Kaggle. The dataset is designed to help agricultural firms model financial risk intelligently. It employs real-world variability by combining financial records, environmental data, and commodity market indices.

Data pre-processing using Handling missing values

In the section, data pre-processing ensures reliable, consistent input for model training by handling missing values using linear interpolation. Sensor faults or missing records can affect model reliability due to missing values in time-series financial records and environmental data. The issues were addressed by employing linear interpolation to impute missing values by linking nearby known points with a straight line, where continuity is maintained and the performance of the Attention-based LSTM model is enhanced. The linear interpolation is given in Equation (1):

$$f(x) = b_0 + b_1(x - x_0) \quad (1)$$

Where x_0 refers to the previous known time step, x denotes the independent variable, $f(x_0)$ indicates the known dependent variable at x_0, and f(x) represents the interpolated value at time x. The coefficients b_0 and b_1 are determined in equations (2-3):

$$b_0 = f(x_0) \quad (2)$$

$$b_1 = \frac{f(x_1) - f(x_0)}{x_1 - x_0} \quad (3)$$

Where b1 denotes the rate of change between two known data points. Linear interpolation accurately recovered handling missing data, maintained temporal continuity, and improved data completeness, ensuring smoother input sequences and enhancing the training accuracy and stability.

Sooty Tern Optimization Algorithm Attention-Based Long Short-Term Memory (STOA-Att-LSTM)

In the section, the framework STOA-Att-LSTM enhances hyper-parameters to improve the predictive accuracy of agricultural risk assessments while integrating LSTM for sequential financial risk learning and attention to enable feature focus.

Attention-Based Long Short-Term Memory (Att-LSTM)

The Att-LSTM model includes two components: the LSTM layer and the attention mechanism. This combination improves the model's capacity to selectively highlight the most pertinent elements in sequential financial, meteorological, and market information as well as capture long-term temporal connections. The LSTM layer has been developed to process sequential data by storing important past data and forgetting unimportant past inputs. The LSTM layer is characterized by three non-linear gates: the input gate, the output gate, and the forget gate are described in equations (4-9). The input gate controls how much new information is let into the memory cell:

$$i_j = \sigma\left(W_i\left[h_{j-1}, x_j\right] + b_j\right) \quad (4)$$

The information from the previous cell state that should be erased is determined by the forget gate:

$$f_j = \sigma\left(W_f\left[h_{j-1}, x_j\right] + b_f\right) \quad (5)$$

A candidate memory content is computed using a hyperbolic tangent function:

$$\widetilde{C_j} = tanh\left(W_C\left[h_{j-1}, x_j\right] + b_c\right) \quad (6)$$

The new candidate content and the previously stored memory are then combined to update the cell state:

$$C_j = f_j \otimes C_{j-1} + i_j \otimes \widetilde{C_j} \quad (7)$$

The output gate regulates the exposure of memory content to the next time step:

$$o_j = \sigma\left(W_o\left[h_{j-1}, x_j\right] + b_o\right) \quad (8)$$

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Finally, the hidden state output is computed as:

$$h_j = o_j \otimes tanh\ tanh\ (C_j) \qquad (9)$$

Where, $[h_{j-1}, x_j]$ indicates the concatenated vector, W_i, Wf, W_C, W_o states weight matrices, ⊗ indicates element-wise multiplication, hyperbolic tangent activation represented by tanh, the sigmoid activation function is denoted by σ , b_j, bf, b_c, b_o are corresponding biases.

To enhance the performance of the model, an attention mechanism is added after the LSTM layer. The attention layer enables the model to adjust the target important elements of the input sequence by weighting every hidden state output. The attention process is defined in equations (10-12):

$$M = tanh\ tanh\ (W_h H \oplus W_u u_a \otimes e_n) \qquad (10)$$

$$\propto = softmax(w^T M) \qquad (11)$$

$$r = H \propto^T \qquad (12)$$

The network efficiently extracted long-term dependencies and emphasized key time-series features, leading to enhanced accuracy, interpretability, and robustness for forecasting financial risk in agricultural businesses.

Sooty Tern Optimization Algorithm (STOA)

The STOA is a metaheuristic optimization method that aims to optimize the performance employed in predicting financial risk for agricultural businesses. Adapted from ST' migration and attacking behaviours, STOA performs well in balancing exploration and exploitation under high-dimensional search spaces. STOA is implemented to dynamically adapt the hyper-parameters such as learning rate, LSTM units, dropout rate, and attention weights, under dynamic climatic and market conditions.

Migration Behaviour (Exploration phase)

The algorithm's ability to search or explore globally is shown in the three stages of ST migration behaviour is described in equations (13-17).

Collision Avoidance

To avoid overlapping in the search space, agents update their positions based on a dynamic adjustment factor:

$$C_{st} = SA \cdot P_{st}(j) \cdot Z \qquad (13)$$

Where Z denotes current iteration, C_{st} indicates the updated position, P_{st} (j) represents the current position of j^{th} search agent. The search agent SA movement factor is calculated as:

$$SA = C_f \cdot \left(1 - \frac{Z}{MaxIterations}\right) \qquad (14)$$

$$Z = \{0,1,2, \ldots, MaxIterations\} \qquad (15)$$

Where C_f denotes a control factor.

Directional Convergence towards Best Neighbour

Once collision avoidance is addressed, each search agent adjusts its position toward the globally best-performing agent:

$$M_{st} = C_B \cdot (P_{bst} - P_{st}) \cdot Z \qquad (16)$$

Where, CB=0,5 ·Rand with Rand∈[0,1], M_{st} symbolizes the motion toward the best neighbor, P_{bst} indicates the best agent's position.

Position Update Based on Both Factors

The combined position update is defined as:

$$D_{st} = C_{st} + M_{st} \qquad (17)$$

This update represents the new position of each agent in the population to explore the hyper-parameter space for better Att-LSTM configurations.

Attacking Behaviour (Exploitation Phase)

In the exploitation stage, agents simulate the spiral descent of sooty terns when attacking prey. This fine-tuning helps in the local optimization of promising solutions. The spiral trajectory is mathematically represented in equations (18-20):

$$x_0 = Radius \cdot sin\ sin\ (i) \quad (18)$$
$$y_0 = Radius \cdot cos\ cos\ (i) \quad (19)$$
$$z_0 = Radius \cdot i \quad (20)$$

Where sin sin (i) and cos cos (i) denotes sine and cosine of iteration index i.

The spiral radius is defined in equation (21):

$$Radius = u \cdot e^{kv} \quad (21)$$

Here, i∈[0,2π], u=1,v=1, and e denotes the Euler's number. The final position of the search agent is updated in equation (22):

$$P_{st}(Z) = Z \cdot D_{st} \cdot (x_0 + y_0 + z_0) \cdot P_{bst}(Z) \quad (22)$$

STOA optimally tuned hyper-parameters efficiently, leading to enhanced prediction accuracy, faster convergence speed, and adaptive financial risk prediction in farm businesses under dynamic economic and environmental conditions. The STOA-Att-LSTM architecture predicted agricultural financial risk with enhanced accuracy by dynamically focusing on essential aspects and improving learning parameters for greater generalization and resilience.

RESULTS

The STOA-Att-LSTM system integrates the STOA, LSTM, and Att mechanisms to model temporal relationships and maximize performance for real-time financial risk prediction in agricultural enterprises. Implemented in Python 3.11.4, the model was tested on a high-performance setup, Windows 11, ensuring efficient, scalable risk predictions and robust handling of diverse financial, climatic, and market data in dynamic agricultural contexts.

Performance Analysis

In the section, Accuracy and Precision measures compare STOA-Att-LSTM against an Artificial Neural Network (ANN)[12] and Decision Tree (DT)[12] baselines. ROC analysis and Revenue vs Expenses visualization confirm the model's better classification performance and financial risk alignment in agricultural settings. Table 1 presents comparative outcomes across various models.

Table 1. Performance Comparison across various approaches

Models	Accuracy	Precision
ANN[12]	0,9637	0,9660
DT[12]	0,9778	0,9869
STOA-Att-LSTM (proposed)	0,9899	0,9889

Accuracy

The ratio of accurate financial risk level predictions (Low, Medium, and High) to each of the model's projections is known as accuracy. It measures the overall performance of the classification model in its ability to predict the right class for all instances. Accuracy can be calculated in equation (23):

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (23)$$

Precision

Precision measures the ratio of actual positive predictions to all enterprises labelled as high-risk. It particularly indicates the model's capability to prevent false alarms in financial risk identification. Precision can be calculated in equation (24):

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$$Precision = \frac{TP}{TP+FP} \quad (24)$$

The comparison of (a) accuracy and (b) precision across various models is depicted in figure 2.

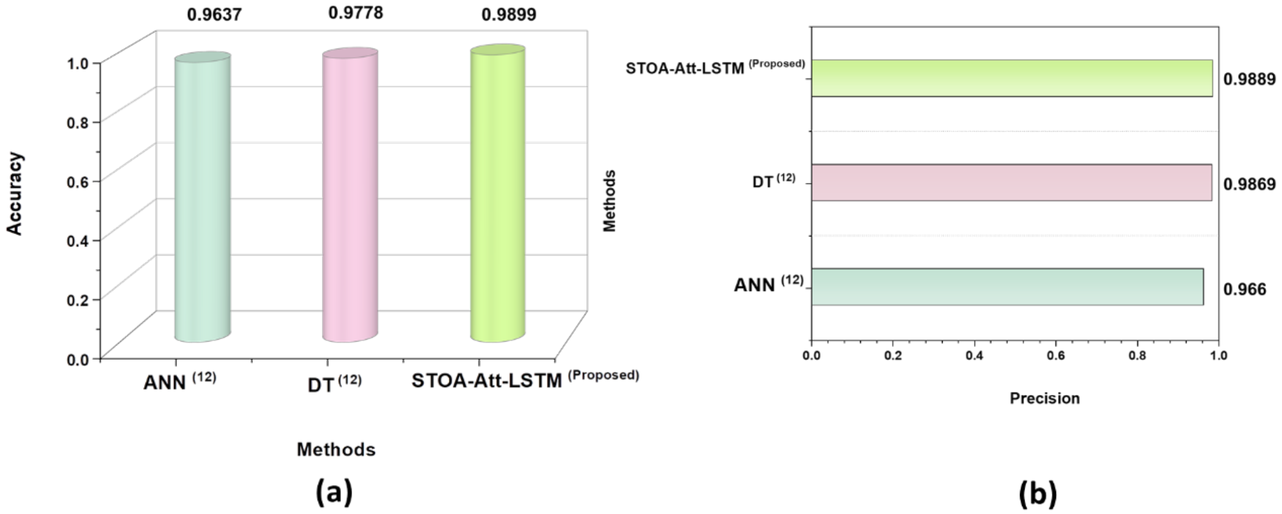

Figure 2. Visualization of (a) Accuracy (b) Precision

The suggested framework reached an accuracy of (0,9899) and greatly outperformed conventional models such as ANN (0,9637) and DT (0,9778), along with improved precision of 0,9889, then the ANN model (0,9660) and outperformed DT (0,9869), reflecting its robust capability of well-identifying high-risk financial cases with few false positives on agricultural datasets.

Revenue Vs Expenses Coloured by Risk Levels

The scatter plot displays the financial performance of agricultural businesses, showing how revenue and expenses relate to levels of risk by colour. Highly risky entities tend to plot where expenses are greater than revenue, and low-risk entities are grouped where revenue is equal to or higher than expenses. Medium-risk instances are more scattered. Figure 3 depicts the risk levels based on revenue and expenses in agribusiness.

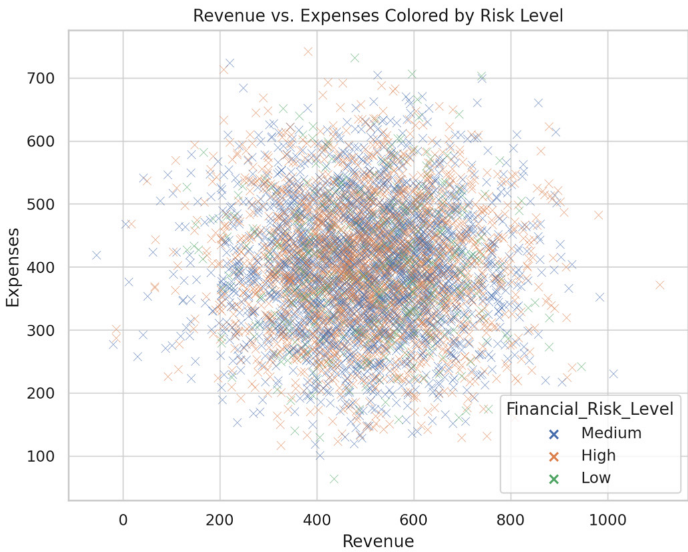

Figure 3. Revenue vs Expenses Coloured by Risk Level

The trend is clear in showing how much revenue and expense figures play a role in forecasting financial risk, validating the STOA-Att-LSTM model's ability to grasp intricate, non-linear financial connections for effective classification.

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DISCUSSION

Traditional models such as ANN[12] and DT[12] suffer from overfitting, sensitivity to noise, and poor handling of nonlinear, imbalanced agricultural data. To overcome the challenges, the model proposed utilizes STOA-based hyper-parameter optimization, LSTM for learning sequential patterns, and attention mechanisms to dynamically weight important temporal features, yielding increased prediction accuracy, robustness to heterogeneous data, and sensitivity to environmental and market changes.

CONCLUSIONS

Research developed a new STOA-Att-LSTM model for forecasting financial risk for agricultural businesses by combining DL with metaheuristic optimization. Various inputs were pre-processed through linear interpolation. The model exploits the LSTM capability to learn sequential dependencies in addition to an attention mechanism for focusing on significant temporal features, while STOA gives optimal feature selection and hyper-parameter optimization. The proposed STOA-Att-LSTM model reached 0,9889 in precision, and 0,9899 in accuracy, demonstrating high reliability in agricultural financial risk prediction. Results presented improved accuracy, adaptability, and generalizability compared to baseline models. Despite concerns of generalizability and heterogeneity of data, the solution provides a scalable proposition. Future research will entail the integration with real-time data and expansion to more general agri-finance uses.

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Authors declare that there is no conflict of interest.

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