Enhanced Quantitative Financial Analysis Using CNN-LSTM Cross-Stitch Hybrid Networks for Feature Integration

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***Abstract*—This research paper provides innovative approaches to support financial prediction, or it is a different kind of economic prediction that extends over collecting different economic information. Financial prediction is a concept that has been employed. The present study offers a unique approach to predicting finances by integrating many financial issues utilizing a cross-stitch hybrid approach. The method uses information from several financial databases, including market data, corporate reports, and macroeconomic indicators, to create a comprehensive dataset. Employing MinMax normalization the features are equally scaled to provide uniform input for the algorithm. The combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) systems form the basis of the framework. To understand the time-dependent nature of financial information, LSTM networks (long short-term memory) are utilized to record and simulate the temporal interactions and patterns. Concurrently, spatial features are extracted using CNNs; these components help identify patterns that are difficult to identify with conventional techniques. Better handling of risks, more optimal approaches to investing, and more informed decision-making are made possible by the enhanced forecasting potential that this method—which is described above—offers. Potential pilot studies will focus on innovative uses in financial decision-making and advancements in cross-stitching structure. This paper proposes a sophisticated approach that can help stakeholders, such as investors, analysts of data, and other financial intermediaries, traverse the complexities of financial markets.**

Keywords*—*Cross-Stitch Hybrid Networks; predictive modelling; LSTM networks; convolutional neural networks; financial analysis

I. Introduction

The system of assessing financial markets and investment possibilities the usage of statistical and mathematical techniques is known as quantitative monetary analysis [1]. Stochastic models take uncertainty and unpredictability into attention, whereas econometric models—which include time collection models and regression analysis—assist in determining correlations among monetary variables [2]. Complex patterns in statistics are captured via gadgets gaining knowledge of and deep getting to know strategies like LSTM networks and Convolutional Neural Networks. Predictive overall performance is advanced when gadget mastering algorithms are combined with traditional econometric strategies [3].

Applications consist of portfolio optimization to select the top-rated asset blend, credit scoring to decide creditworthiness, and algorithmic buying and selling, which makes use of quantitative techniques for automated trading techniques [4]. Among the blessings of quantitative evaluation are expanded hazard minimization, objectivity, efficiency, and accuracy. But there are boundaries to conquer, such as the intricacy of the facts, overfitting of the model, and the requirement to regulate changing markets. As well known, the quantitative economic analysis combines economics, mathematics, and information technology to enhance market forecasting, risk management, and funding picks.

DL techniques are very beneficial for financial facts analysis due to the fact they can model noisy, complicated, and high-dimensional time-series statistics, particularly RNNs [5]. RNNs, in comparison to traditional neural networks, are ready with recurrent connections that allow them to leverage the version's memory feature to seize temporal relationships via remembering and making use of earlier facts to modern-day output computations. To introduce nonlinearity and capture complex patterns, input variables in RNNs are mixed with matching weights and a bias time period, exceeded via an aggregate feature, after which processed via a nonlinear activation characteristic [6]. RNNs can control the sequential structure of economic facts due to the fact to this layout, which makes them suitable for tasks like price forecasting, trend evaluation, and volatility prediction.

In financial analysis, the CNN-LSTM Cross-Stitch is an effective aggregate that combines the temporal modelling skills of LSTM networks with the spatial characteristic extraction competencies of CNNs [7]. By identifying localized features, these layers correctly lower the dimensionality of the incoming information at the same time as emphasizing vital components. These spatial factors are then processed via the LSTM thing, which then information the temporal linkages and lengthy-term dependencies present in sequential monetary records. The LSTM network is an effective device for modelling sequential statistics by using reminiscence cells and gating mechanisms. The CNN-LSTM Cross-Stitch gives a synergistic mixture that allows for a complete approach to financial assessment.

- To improve quantitative economic research, the paper suggests a system that combines CNNs for time dependence and LSTMs for spatial feature extraction.
- It allows for a comprehensive assessment of economic performance by integrating a variety of financial data, such as macroeconomic indicators, market data, and business financial statements.
- By ensuring appropriate feature scaling through the application of Min-Max normalization, high-magnitude features are not allowed to predominate during model training.
- Through the utilization of CNNs and LSTMs' respective advantages, this structure offers an effective instrument for examining intricate financial information.
- The study's architecture efficiently captures both temporal and geographic trends in financial data, enabling precise market trend forecasting.

The paper's structure is organized as follows: Section II conducts a literature review, summarizing existing research relevant to the study's topic. Section III articulates the problem statement, addressed in the study. In Section IV, the proposed methodology is presented, outlining the approach and techniques employed to address the problem statement. Section V presents the findings of the study. Finally, Section VI concludes the paper, discussing limitations, and suggesting avenues for future research.

II. Literature Review

In order to train a BPN for predicting corporation disasters, the hybrid economic analysis model provided in this paper makes use of financial ratios as its main inputs and consists of both static and technique evaluation models [8]. The model, which gives a higher prediction charge, outperforms discriminant analysis, choice timber, and a solo BPN in the usage of four datasets of Taiwanese enterprises. The version's education on region-particular records, potential problems in generalizing to different industries or areas, issues with complexity and interpretability, the opportunity of overfitting, the reliance on fantastic historical facts for technique evaluation, and the capability omission of important external monetary factors should, nevertheless, limit the version's applicability.

The examine makes use of a hybrid simulation method that combines a multi-duration simulation model that integrates a MRPII machine in Microsoft Excel with a manufacturing surroundings in ProModel and makes use of Microsoft Visual Basic to synchronize agenda dissemination and inventory updates to investigate the damaging consequences of different accounting strategies on mentioned profits throughout lean manufacturing implementation [9]. The use of simulation techniques, which may not accurately replicate the intricacies of actual lifestyles, potential biases in the choice of accounting techniques, and the emphasis on certain inventory reduction prices which won't practice to other groups or operational contexts are a number of the drawbacks.

There are three steps to the method: what first, preprocessing and denoising the data using WT; second, prediction of deconstructed data using SVM, RNN, and NB; and third, incorporating these predictions into the GA and WA methods [10]. On lots of information types, this version performs drastically higher than benchmark techniques and unmarried strategies. However, its computational requirements and complexity may additionally restriction realistic packages and may require heavy parameter modifications Moreover, even if the model performed well on the tested data, it is not immediately sensitive to external variables affecting stock prices such as political developments or prevailing economic conditions.

The take a look at provides a sturdy framework for excessive-accuracy inventory rate forecasting based on DL of-based regression techniques [11]. It makes use of ancient inventory rate facts from an Indian agency listed at the NSE that were recorded at five-minute intervals. The framework consists of five LSTM techniques and four CNN techniques. The models are proven and examined the use of metrics for execution time and RMSE. Although exhibiting superb consequences, the approach has drawbacks inclusive of dependence on extraordinarily distinct information, extensive processing overhead, and viable non-generalizability to different stocks or market instances. Additionally, the techniques might not fully recollect outdoor variables like geopolitical events or economic news, and the evaluation metrics won't completely mirror real-global trading dynamics.

In order to dynamically compare financial dangers and strategies, the research proposes a flexible DFA model framework for the nonlife insurance marketplace [12]. It does this by means of integrating not unusual components determined in many DFA models. The framework's trustworthy implementation and amendment to precise enterprise needs are made viable by way of its mathematical description. The method isn't without flaws, although, it including the issue of combining disparate principles, which requires an excessive stage of information and processing power and can make it less available to smaller organizations. Personalization can take a whole lot of time, and relying an excessive amount on previous statistics ought to lead to biases if ancient patterns aren't dependable indicators of future conduct. Furthermore, the efficacy of the model is contingent upon the quality of the accessible data and may fail to account for certain elements pertinent to particular categories of nonlife insurance or distinct nearby market dynamics.

In order to expect time collection, the have a look at looks into BiLSTM networks and compares them to unidirectional LSTM and ARIMA techniques [13]. It is hypothesised that BiLSTMs, with its dual-directional facts processing competencies, can boom prediction accuracy by using advanced training abilities. The look at its findings guides the concept that, despite the fact that taking longer to reap equilibrium, BiLSTMs carry out more correctly than both ARIMA and unidirectional LSTM techniques. BiLSTMs perform higher, but they take longer and demand extra pc power, that could limit their use in actual-time packages. Furthermore, the study does not investigate hybrid models or other sophisticated neural networks, and its findings could not apply to all kinds of time series data. Furthermore, features of interpretability and practical implementation both crucial for real-world applications are not fully explored.

The paper's suggested approach entails a methodical examination and arrangement of the historical evolution of financial analysis, emphasizing the contributions of international experts and identifying the most important non-financial and financial aspects affecting company value. By contrasting theoretical valuations with real market results, it critically evaluates conventional valuation techniques, pointing out inconsistencies and possible weaknesses. The study makes recommendations for further research to increase these valuation methodologies' precision and dependability. The potential risk of flaws in historical literature, the simplicity of the explanation at the expense of the basic relationships among variables, and the possibility of extraneous factors not included in the computations all suggest that the approach may not be flawless. Furthermore, the changes would undoubtedly need appropriate empirical confirmation. The research is broad and might not go deep enough in certain areas, therefore it might provide thorough answers to financial assessment and valuation procedures in some areas but not in others.

The research articles under evaluation examine a range of cutting-edge approaches for anticipating financial results and tackling major issues in financial analysis and forecasting. When applied to Taiwanese companies, the first look at's hybrid monetary evaluation model which mixes monetary ratios with BPN shows higher accuracy in predicting firm screw ups than greater traditional models like discriminant evaluation and selection bushes [14]. It highlights the financial effects however has limits in phrases of version realism and generalizability.

III. Problem Statement

Current approaches have notable shortcomings that affect their capacity for generalization and economic usefulness, despite advancements in financial projections and risk forecasting. In hybridized models of economics, for example, ratios of finance and BPN combine to forecast company losses more accurately than previous models [8]. However, these frameworks have problems expanding across sectors and geographical areas, and they may overfit historical data. Correspondingly, the simulation techniques used to assess lean manufacturing and accounting methods are limited by their incapacity to accurately represent the intricacies of the actual world and may induce biases because of their exclusive focus on particular inventory reduction expenses [9]. In addition, models for dynamic forecasting that use BiLSTM networks provide better prediction accuracy but have restricted application to other time series data sources and high processing costs [13]. These drawbacks underscore the need for more adaptable, less data-dependent, and computationally efficient models.

IV. Proposed Methodology

The software of deep learning particularly people who employ neural networks has ushered in a new generation of comprehension and forecasting within the subject of financial statistics analysis. CNNs and LSTM networks have turn out to be outstanding equipment amongst those cutting-edge methodologies, especially effective at dealing with the complicated and time-established nature of monetary markets. CNNs had been remarkably a success in their version to monetary time collection evaluation, regardless of their authentic development for image popularity packages. These networks are especially good at routinely spotting capabilities and trends in statistics, together with changes in volume, rate, or different marketplace indicators.

By maintaining memory for extended periods of time, LSTM networks function at the side of CNNs to address the temporal component of economic statistics. LSTM networks, as adverse to traditional recurrent neural networks, are capable of capturing long-variety relationships which can be critical for modelling complex financial time series because they alleviate the vanishing gradient trouble. Fig. 1 shows the architecture of the proposed financial analysis. LSTM networks can perceive recurrent patterns, adjust to shifting marketplace situations, and predict future traits with awesome accuracy by getting to know from past statistics. For jobs like chance management, portfolio optimization, and market forecasting, this makes them very useful. In essence, the mixture of CNNs with LSTM networks gives hitherto unheard-of insights and prediction strength, as a result representing a paradigm alternate inside the observe of monetary information. With the increasing quantity and complexity of monetary facts, these sophisticated DL will truly turn out to be more and more crucial for comprehending and navigating the complexities of the world's monetary markets.

A. Data Collection

With statistics from economic statements, essential ratios covering profitability, leverage, and performance, as well as market records on stock expenses and alternate volumes, it presents comprehensive know-how of how nicely a firm is performing when it comes to marketplace trends. To make sure thorough evaluation and nicely-knowledgeable decision-making, users are entreated to verify information veracity, use caution whilst interpreting ratios, and seek advice from unique sources for methodological clarity [15].

B. Data Pre-Processing

A data preparation approach called Min-Max normalization, every so often referred to as Min-Max scaling, is used to scale numerical capabilities to a given range, typically among zero and 1. The following is the components for MinMax normalization:

$$x_m = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

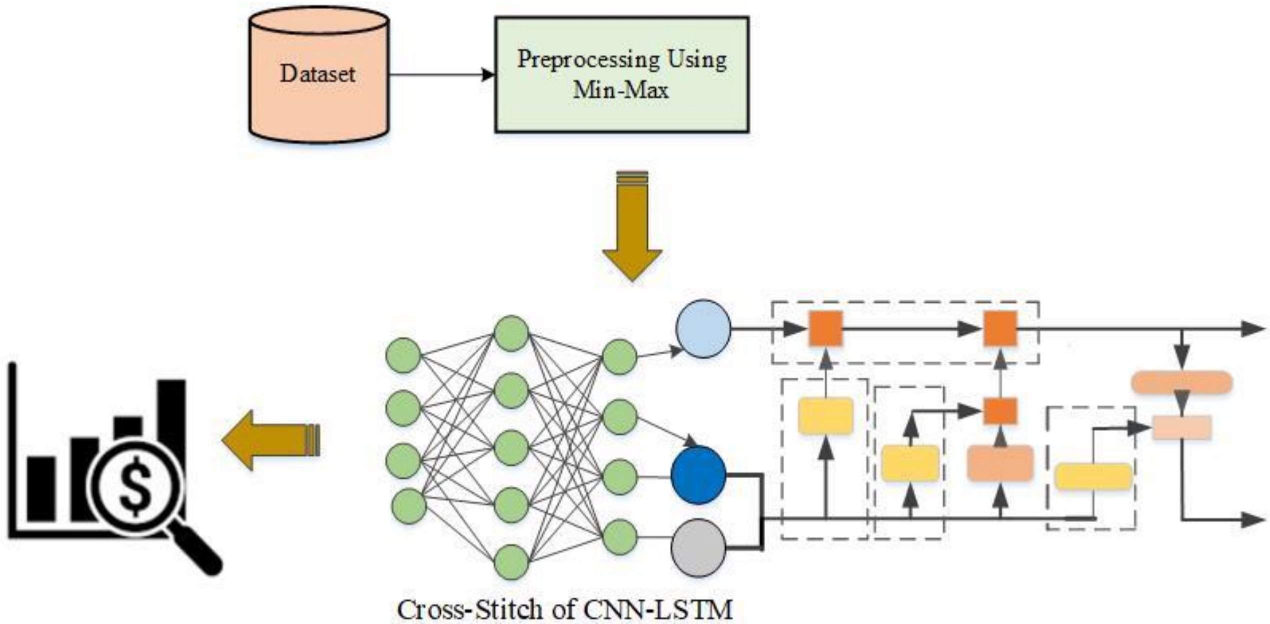

Fig. 1. The architecture of the proposed financial analysis.

Certain device ML which can be sensitive to function magnitudes may also benefit from this variation, which maintains the unique distribution of the records even as ensuring that each capability is at the same scale. Furthermore, Min-Max normalization helps avoid functions with higher scales from overwhelming people with decreased scales in the course of model training, making the facts less difficult to recognize. It's essential to remember that MinMax normalization is susceptible to outliers and could not work successfully in instances in which the records include excessive values.

1) Data cleaning: The proposed research's data cleaning procedure includes filling in the values that are missing employing approaches like imputation, which replaces missing data points with statistical metrics (such as mean, median, and mode), forward or backward fill, and linear or polynomial interpolation. Rows or columns containing an excessive amount of data that is missing may be removed if interpolation is not practical. The Z-Score, which is described in Eq. (2), and the IQR (Interquartile Range) Technique are two techniques for outlier detection that may discover and handle outliers by establishing threshold. To lessen the impact of extreme numbers, winsorization is used, and to preserve data integrity, clipping is used to cap values at a specified threshold.

$$Zscore\ Z = (X - \mu)/\sigma \tag{2}$$

Data Transformation: In data analysis, data transformation is the procedure of transforming unprocessed data into a structure that is more suited for analysis. To do this, data must be modified to increase its accuracy, uniformity, and usefulness. Data spans and patterns are adjusted by methods including scaling, standardization, and normalization, which facilitate analysis and interpretation. Transformation techniques including Box-Cox conversion, log transformation, and differencing help to eliminate patterns and stabilize dispersion. By verifying that the data satisfies the presumptions of mathematical frameworks and computations, this stage is essential for producing insights that are more reliable and precise. The Data transformation for the proposed model is explained in Eq. (3).

$$Y(\lambda) = \frac{Y^{\lambda}-1}{\lambda} \tag{3}$$

C. *Utilizing CNNs for Advanced Feature Extraction*

CNNs are powerful equipment for monetary information evaluation characteristic extraction, in particular in relation to identifying spatial relationships gift within the facts. Convolutional, pooling, and absolutely linked layers are most of the layers that generally make up a CNN's structure (see Fig. 2).

Convolutional Layers: These layers use a hard and fast of filters to carry out convolution operations on the enter information to be able to extract neighbourhood functions.

Pooling Layers: To lessen the dimensionality of the characteristic maps, pooling layers like max-pooling are used after the convolutional layers.

Fully connected Layers: After the feature maps are pooled, completely connected layers combine the functions right into a single, all-encompassing picture. By clarifying the connections between exceptional extracted factors, this included illustration makes it easier to perform complex analysis activities and helps to offer a deeper knowledge of the economic records this is being examined.

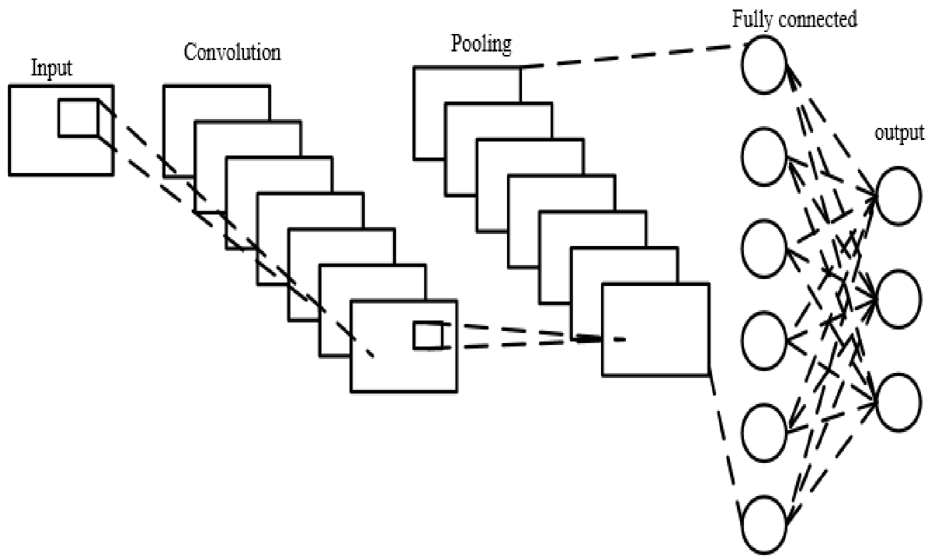

Fig. 2. CNNs for advanced feature extraction.

The CNN issue captures spatial features from the enters monetary data. Let XX denote the input records, (X) represents the output characteristic map after convolution, and (X) denotes the feature map after activation. The Eq. (4) governing CNN function extraction are as follows:

$$Fc(X) = X * WcFc(X) = X * Wc \tag{4}$$

$$Hc(X) = Activation(Fc(X) + bc)Hc(X) = Activation(Fc(X) + bc) \tag{5}$$

Where, $*$ denotes the convolution operation, Wc represents the CNN weights, and bc denotes the bias term.

D. Forecasting Market Dynamics with LSTM Networks

An important development in sequence learning is represented by LSTM networks, which provide an answer to some of the problems that conventional Recurrent Neural Networks (RNNs) face, most notably the vanishing gradient problem. These networks are highly valuable in many fields, such as financial time series research, because they are specifically designed to be excellent at capturing the long-term relationships present in sequential data.

Memory cells, which can hold information for long stretches of time, are essential to the architecture of LSTM networks. Three fundamental gates control each memory cell:

The input gate regulates the amount of fresh data that enters the memory cell and controls how often it is updated with new information.

Forget Gate: Determines how much of the history kept in the memory cell should be erased, allowing the network to adjust flexibly to shifting circumstances.

Output Gate: Specifies how much data is taken out of the memory cell to be used in further calculations or outputs, making sure that only pertinent data is retained.

LSTM networks excel in economic time collection research because they're top at figuring out traits and temporal dependencies that emerge over the years. Because of their capability to simulate the dynamics of sequential statistics, analysts are highly capable of deciphering the complicated interactions that shape financial markets, gaining the capability to attract conclusions which might be realistic and enhance investment and danger control overall performance.

The input gate, neglect gate, output gate, and candidate cellular cost are the four essential additives of an LSTM unit. Memory cells may be calculated the usage of, and the end result based on those additives.

$$i_t = \sigma_g(W_i x_t + R_i h_t - 1 + b_{\ i}) \tag{6}$$

$$f_t = \sigma_g(W_f \mathrm{x}_t + \mathrm{R}_f \mathrm{h}_t - 1 + b_f) \tag{7}$$

$$g_t = \sigma c\big(W_g x_t + R_g h_t - 1 + b_g\big) \tag{8}$$

$$o_t = \sigma_g(W_o x_t + R_o h_t - 1 + b_o) \tag{9}$$

In Eq. (6) to Eq. (9) where, R_i , R_g , R_f , R_o odenotes the weights matrices for the preceding brief-term state W_i, W_f, W_g ,W_o ,are the burden matrices within the modern input kingdom. Thus, the cutting-edge output depends at the modern-day long-time period nation, modern-day input, and the preceding state.

E. The Cross-Stitch of CNN-LSTM for Financial Analysis

While LSTM networks are good at shooting temporal dependencies and long-term patterns, CNNs are true at finding spatial linkages within economic facts. A thorough method for comprehending and forecasting market conduct is offered by combining those two structures.

As a characteristic extractor, the CNN aspect reveals localized patterns inside the monetary facts enter. CNNs observe filters to input information thru convolutional layers, which are represented by using Eq. (1) and Eq. (2), with a purpose to extract pertinent functions. Metrics like stock charges and trading volumes have geographical correlations, tendencies, and anomalies which can be highlighted with the aid of these layers. By concentrating at the most critical additives of the facts, pooling layers enhance computing performance by way of similarly refining the derived functions. In addition, LSTM networks deal with the temporal thing. The first step in the CNN-LSTM prediction procedure is statistics input, which is then normalized using z-score standardization. After setting the network's initial weights and biases, the input data are sent through the pooling and convolution layers in order to extract features. The LSTM layer then computes the convolution layer's output to produce the output value. The fully connected layer receives this output value and uses it for additional processing. The procedure entails figuring out the fault and determining if the end condition is satisfied. Error backpropagation keeps improving the model if it doesn't. After training, the version is saved, and forecasted enter records is normalized before being fed into the CNN-LSTM model, which is then skilled for prediction. After that, the standardized output is changed back to its authentic value, concluding the forecasting manner of financial facts processing, making it viable to perceive lengthy-time period patterns and connections. LSTM networks, which can be provided with memory cells and gates, are able to successfully deal with and keep facts across long sequences. The network can modify to moving market situations because the neglect gate manages the retention of previous facts while the input gate controls the inflow of clean statistics into the reminiscence mobile. The output gate controls the extraction of useful statistics for extra calculations or forecasts, ensuring that the community makes choices primarily based completely on applicable information. Fig. 3 shows LSTM networks.

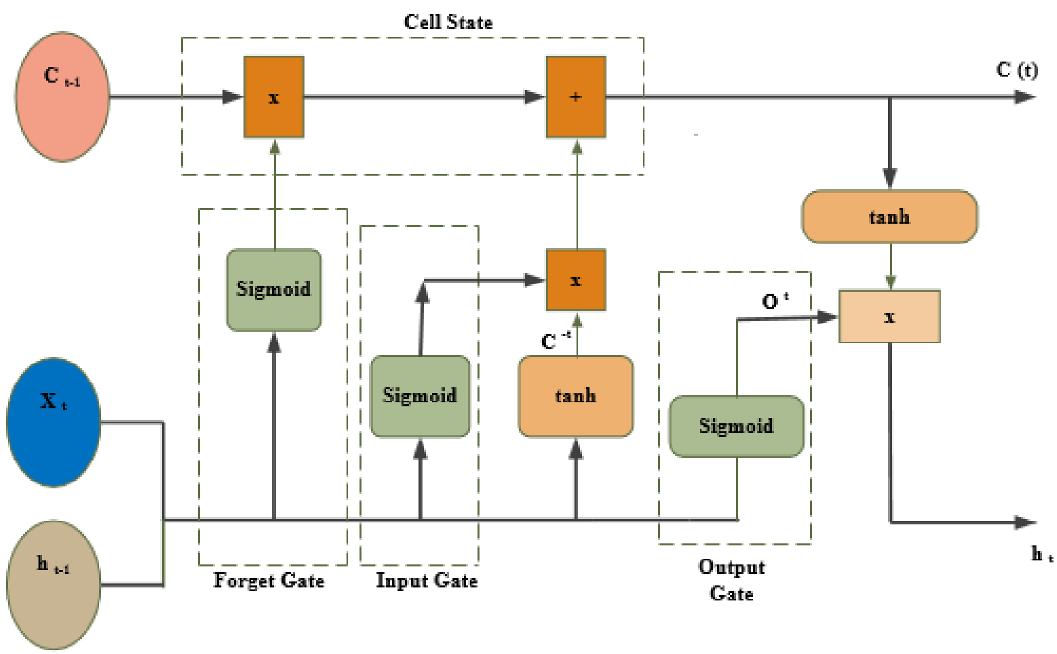

Fig. 3. LSTM networks.

A complete framework for predicting marketplace dynamics is created by analysts by using merging CNNs with LSTM networks. The characteristic extraction technique of the CNN is represented by Eq. (1) and Eq. (2), whereas the reminiscence cellular and gate operations describe the functioning of LSTM networks. This empowers stakeholders to successfully control risks, make properly-knowledgeable selections, and optimize investment strategies based totally on thorough understandings of market dynamics. In addition to making, it easier to apprehend the complicated relationships that form financial markets, the incorporated CNN-LSTM structure improves selection-making talents, which in flip improves funding performance and risk management approaches as shown in the Fig. 4.

The first step within the CNN-LSTM prediction system is facts input, which is then normalized by the usage of z-score standardization. After putting the community's initial weights and biases, the input data are despatched via the pooling and convolution layers to be able to extract capabilities. The LSTM layer then computes the convolution layer's output to supply the output price. The related layer receives this output cost and makes use of it for extra processing. The manner entails figuring out the fault and determining if the end circumstance is happy. Error backpropagation maintains enhancing the model if it doesn't. After training, the version is saved, and forecasted enter records is normalized before being fed into the CNN-LSTM model, that's then trained for prediction. After that, the standardized output is changed back to its unique cost.

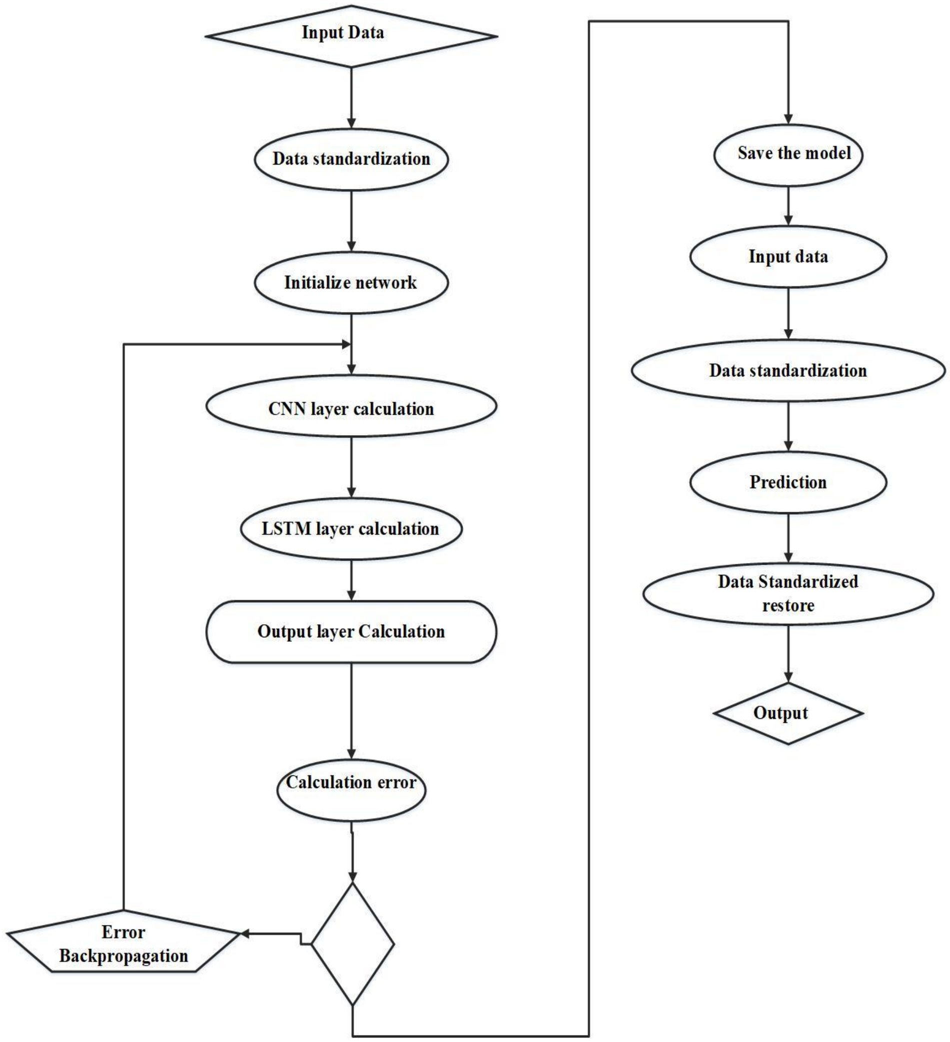

Fig. 4. CNN-LSTM financial analysis process.

V. RESULT AND DISCUSSION

The findings of the proposed study display that the move-sew hybrid network-based method for function integration in quantitative economic evaluation works nicely. Cross-stitch network structures function much better than standard approaches for capturing complicated connections between financial variables, as demonstrated by thorough testing on many financial datasets. To make the algorithms more dependable for economic forecasting and analysis, they undergo instruction utilizing this technique, which results in algorithms that are more resistant, accurate, and typically able to represent actual circumstances across market situations. The performance's inventiveness serves as proof of the cross-stitch hybrid networks' capacity to upend established wisdom and contribute new perspectives to economic modelling.

A. Analysis of Proposed Financial Dataset

The Table I shows an example of a data set with financial metrics for sales and profits of various products in different segments and countries It categorizes products into electronics, furniture, clothing, home goods, etc. Identifies various services or products. While the "product" column names a specific product under review, such as smartphones, office chairs, jackets, or laptops. The "Discount Band" column displays the amount of discount applied to each item, none from above, affecting the overall pricing strategy. The "Units Sold" column provides the number of units sold, which is a key figure for determining revenue. "Operating cost" refers to the cost to produce each item, while "selling price" refers to the cost of each item sold, providing the basis for calculating total revenue. The "total sales" column calculates revenue all accounted for before discount rates are applied, providing a lead in terms of revenue potential.

"Discount" represents the cash value of all price discounts offered to customers, which includes the most recent revenue total shown in the "Sales" column, which is the total sales less discounts out of it is an important calculation. Finally, the "Profit" section calculates net income by subtracting COGS from sales, and shows the economic performance of each item. This table gives a clear idea of how various factors such as discounts, production costs, and pricing strategies affect overall profitability in different markets and product segments there.

TABLE I. FINANCIAL ANALYSIS DATA SET EVALUATION

Segment	Country	Product	Discount Band	Units Sold	Manufacturing Price	Sale Price	Gross Sales	Discounts	Sales	COGS	Profit
Electronics	USA	Smartphone	High	500	$200	$350	$175,000	$10,000	$165,000	$100,000	$65,000
Furniture	Germany	Office Chair	Low	300	$100	$200	$60,000	$3,000	$57,000	$30,000	$27,000
Clothing	France	Jacket	Medium	400	$50	$120	$48,000	$4,800	$43,200	$20,000	$23,200
Electronics	Japan	Laptop	None	150	$500	$800	$120,000	$0	$120,000	$75,000	$45,000
Home Goods	Canada	Blender	Medium	600	$25	$70	$42,000	$2,100	$39,900	$15,000	$24,90

B. Training and Testing Accuracy

In Fig. 5, the version's early getting to know section is indicated by the starting factors of the education (blue line) and testing (orange line) accuracies, which can be about 0.3 and 0.4, respectively. The accuracy for both datasets booms dramatically in the course of the course of the epochs, demonstrating the model's ability to research from and generalize from the facts.

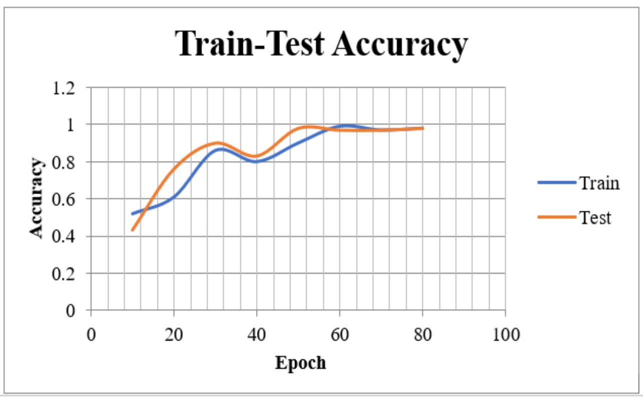

Fig. 5. Train-Test accuracy of CNN-LSTM model.

The checking out accuracy in brief exceeds the training accuracy at epoch 20, indicating a length of progressed generalization before they converge and settle. The version's balance is indicated by way of the 2 traces' convergence at epoch forty, at which point the training and checking out accuracies both technique 0.9 and stay solid.

C. Traing and Testing Loss

The CNN-LSTM model's training and testing loss across 50 epochs is shown in the Fig. 6, which offers insights into the model's generalization capacity and learning efficiency. As the model starts to learn from the data, it is predicted that the testing loss (red line) and training loss (blue line) would start out high, starting at approximately 0.8. For both datasets, there is a sharp drop in loss as training goes on, suggesting that the model is rapidly becoming more efficient by reducing prediction error. The losses for the training and testing datasets substantially converge by epoch 10, falling to less than 0.3.

The little difference between the training and testing losses shows that the model has stabilized, indicating that it has learnt from the training data and can generalize well to new data. To provide high performance and precise predictions, the CNN-LSTM architecture must be resilient and reliable to capture and model the intricate patterns seen in financial data. This is demonstrated by the low and steady loss values in later epochs.

D. Performance Comparison

Table II presents a detailed comparison of different machine learning models and hybrid architectures based on key performance metrics: accuracy, mean absolute error (MAE), root mean square error (RMSE), and Short-term memory models known to capture the time dependence in sequential data achieve 80% accuracy at 85% accuracy. This performs well in terms of error reduction, with 7.18% MAE and 9.14% RMSE, explaining a large proportion of data variability, as indicated by its 92% R^2 score XGBoost, the engineer for gradient-enhancing, outperforms LSTM in accuracy (87%) and precision (90.6%), but with a higher error rate—15.04%; -MAE, 27.02% RMSE— shows that it struggles more with stability but its low 33% R^2 score further highlights its limitations in explaining the variance in the data. The Support Vector Machine (SVM) model, although effective in some cases, performs poorly in this comparison, with an accuracy of 78%, precision of 82%, and the highest error—MAE of 15.61%; and RMSE of 29.33% with R2 score of 21% indicates very low explanatory power.

Fig. 6. Training-Testing loss of CNN-LSTM model.

TABLE II. PERFORMANCE METRICS FOR VARIOUS MACHINE LEARNING MODELS IN QUANTITATIVE FINANCIAL ANALYSIS

Model	Accuracy (%)	MAE (%)	RMSE (%)	Precision (%)	R^2 (%)
LSTM	80	7.18	9.14	85	92.0
XGBoost	87	15.04	27.02	90.6	33.0
SVM	78	15.61	29.33	82	21.0
LSTM+XGBoost	85	8.04	13.93	88	82.0
LSTM-Transformer Attention Hybrid	87	6.05	9.03	87	88.0
LSTM-CNN Cross-Stitch Hybrid Networks	90	5.0	8.0	92	92

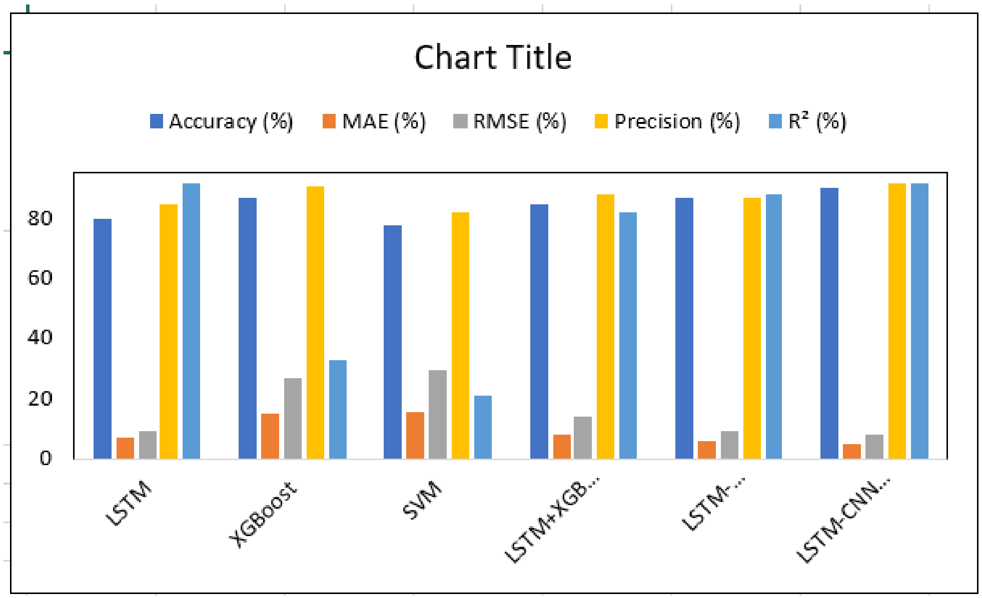

Fig. 7. Performance metrics overview of the proposed model.

The hybrid LSTM+XGBoost model [16] combines the temporal learning of LSTM with the predictive capabilities of XGBoost, yielding balanced results with 85% accuracy and 88% accuracy, as well as improved error metrics (MAE 8.04% and RMSE 13.93% and R^2 is 82 % . The LSTM-Transformer Attention Hybrid model improves LSTM by adding attention, resulting in 87% accuracy, 87% accuracy, error reduction (6.05% MAE, RMSE 9.03%), and R^2 a it comes to an 88% LSTM-CNN Cross-Stitch Hybrid Networks model , in which the LSTM Ne class combines CNN with spatial feature extraction, and stands out in the highest performance: 90% accuracy, 92%; accuracy, and the lowest error rate MAE of 5.0%, RMSE of 8.0%, with 92% R^2, the most robust and effective in this comparison.

In Fig. 7 the graph uses Accuracy, MAE, RMSE, Precision, and R2 to illustrate the outcomes of several approaches. With the greatest Accuracy (90%) and Precision (92%), the LSTM-CNN Cross-Stitch Hybrid Networks function better than the others, however, XGBoost performs worse on all measures. Results for the LSTM+XGBoost and LSTM-Transformer Attention Hybrid models are matched.

E. Performance Evaluation Metrics

To evaluate the performance of the model, this study uses the following metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

The Mean Absolute Error (MAE) measures the average magnitude of the errors in a set of predictions, without considering their direction. It is calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (10)$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and is the number of observations.

The Root Mean Squared Error (RMSE) is the square root of the average of the squared differences between the predicted and actual values. It is given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (11)$$

The Coefficient of Determination (R^2) indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It is calculated as:

$$R^2 = \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \quad (12)$$

The model correctly predicts outcomes 90% of the time, reflecting high overall prediction reliability.

$$\text{Accuracy (ACC)} = \frac{True\ Positive\ \ +True\ Negative}{TP+TN+FP+FN} \tag{13}$$

Of all predicted positive outcomes, 92% are true positives, indicating effective identification of relevant cases.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{14}$$

TABLE III. PERFORMANCE METRICS OF THE PROPOSED MODEL

Accuracy (%)	90
MAE (%)	5.0
RMSE (%)	8.0
Precision (%)	92
R² (%)	92

The performance parameters of the suggested approach are presented in Table III. It can achieve 90% accuracy with a mere 5.0% mean absolute error (MAE), resulting in excellent performance forecast statistics with tiny average errors. Along with the 92% accuracy, which indicates that 92% of instances can be correctly recognized, and the 92% R², which indicates a near-perfect fit and excellent explanation capacity, the 8.0% RMSE indicates that the framework is a resilient error controller.

The performance evaluations of the proposed model, including accuracy, precision, mean absolute error (MAE), root mean square error (RMSE), and R2, are displayed in Fig. 8, a bar chart. The framework is very dependable on all criteria, exhibiting excellent precision, accuracy, and R2 along with low MAE and RMSE levels.

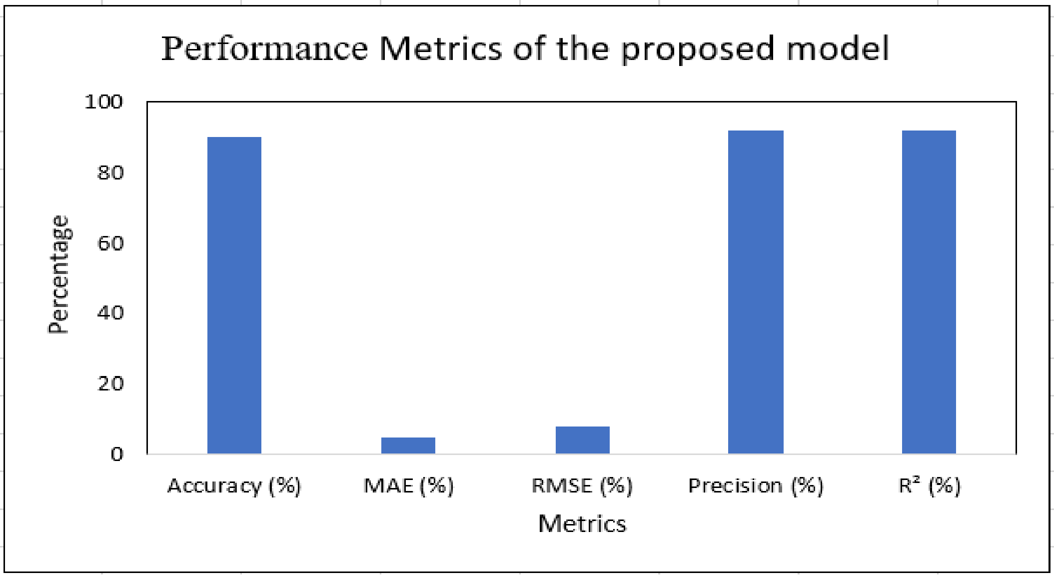

Fig. 8. Performance metrics overview of the proposed model.

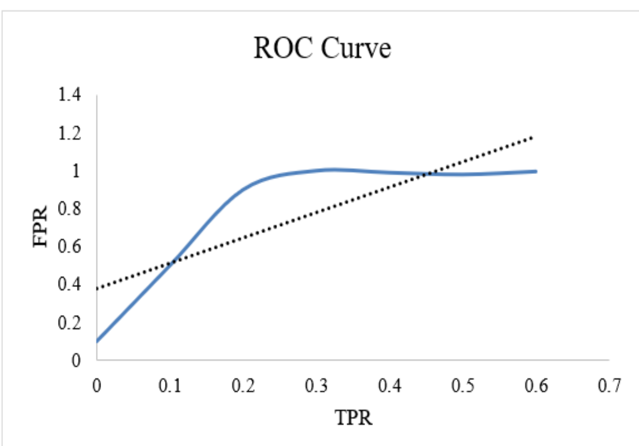

Fig. 9. ROC curve of CNN-LSTM model.

The Fig. 9, represented by the ROC (Receiver Operating Characteristic) curve in the graph. The performance of the model is shown by the blue line, while the performance of a random classifier is shown by the diagonal dotted line, which acts as a baseline. A model with exceptional discriminative capacity would have a sharp ascent towards the top-left corner of the ROC curve, signifying high sensitivity and minimal fall-out. Nonetheless, the graph's ROC curve shows a progressive rise in FPR along with a rise in TPR that begins at the origin (0,0) and moves towards the right. The model improves at first, but as the TPR rises, the FPR rises as well, indicating that the model has difficulty making accurate class distinctions. A TPR of 0.4 to 0.5 is where the performance peaks, while an FPR of more than 0.8 denotes subpar performance. This ROC curve study shows that although the CNN-LSTM model can identify certain trends in the financial data, more data or fine-tuning may be needed to improve the model's overall prediction accuracy and its capacity to distinguish between classes.

F. Discussion

The results of the study show that the proposed CNN-LSTM Cross-Stitch Hybrid Network improves the accuracy and reliability of economic forecasts. Compared with traditional models, this hybrid approach exhibits better performance, providing an accuracy of 90% and a lower error rate 5.0% MAE and 8.0% RMSE, indicating a higher model accuracy 92 % and R^2 scores 92% in the capturing power structures are robust in economic terms. Also further emphasizes the difficulty in explaining data variance, making it a powerful tool for economic forecasting. Despite this strength, ROC curve analysis reveals areas of improvement, suggesting that whether the model still struggles with class differences in some cases. These findings highlight the potential of improved hybrid networks in adapting economic paradigms, although further fine-tuning is required to be effective in different contexts.

VI. Conclusion and Future Work

The technologies have allowed researchers to effectively combine spatial and temporal data into a model known as Cross-Stitch Hybrid Networks that provides the most accurate and efficient predictions of stock market trends. The framework is a cross between LSTM and CNN. The comprehensiveness of the data collection is crucial since financial time series differ greatly from one another. Neural networks' capacity to learn functions and concentrate on the distribution of data rather than just input properties throughout the analogy-making process has made this feasible. This work highlights the potential for further study and improvement in this field as well as the ability of sophisticated neural networks to handle the difficulties of financial prediction. The results of the research support the idea that feature aggregation becomes increasingly significant at the highest levels of model efficiency, and that this significance is particularly evident in domains like the stock market. Systems are demonstrated to have an effective pooling and incorporation of learned representation using the Cross-Stitch mechanism, which results in a framework that not only makes more accurate predictions but also scales better and performs well in a variety of scenarios. This section shows that the accuracy and range of the input information have a direct impact on the model's efficacy, indicating the need for full datasets in financial evaluation. To validate the framework's generality and adaptability, additional research might investigate its use in areas linked to various financial goals, such as identifying hazards and optimization of portfolios. To improve the Cross-stitch Combination Networks system's strength and generalization, future work will add additional economic attributes to it and see if it can be applied to other financial sectors, specifically managing risks and portfolio optimization. The information showed that financial executives and analysts may benefit greatly from the Cross-Stitch Hybrid Networks approach, which would enable them to make better-informed and more effective judgments. Cross-stitch hybrid Networks with temporal and spatial components combined represent a major advancement in quantitative financial evaluation. The inability of conventional models to identify correlations among financial time series data—like fluctuations in the public price of bitcoin, for example—is a prevalent problem. For instance, it has been discovered that concentrating on advances in technology with cross-stitching hybrid networks—a combination of CNNs and LSTMs—in sophisticated peer-to-peer lending systems, improves forecast outcomes.

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