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Original Article

Business Intelligence in ERP ML-Based Comparative Study for Financial Forecasting

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Abstract: *Financial planning in the modern, dynamic business world is highly important in strategic decision-making. Conventional financial forecasting tools, combined with ERP systems, have characteristic difficulties in coping with the nonlinear, time-dependent, and unstructured nature of financial data. Deep learning (DL) is a potential solution for businesses, as forecasting tools that have high intelligence and accuracy become more in demand in business. The present paper suggests a hybrid CNN-LSTM model to improve the financial prediction capabilities of an ERP-based business intelligence system. Based on the CSMAR data containing more than 54,000 financial statements belonging to A-share listed companies, the method is capable of efficiently coping with both feature extraction using convolutional layers and modeling temporal relations using LSTM. A full preprocessing pipeline-data cleaning, data normalization, and dimensionality reduction with PCA offers the best data quality. Experimental evaluation of R^2, MAE, RMSE and MSE shows that the model has a high quality of performance with an R^2 of 0.92 and a low MAE of 0.036 as compared to other models like the random forest model and LSTM model. Following the investigation, the findings reveal that the model can be instrumental in coming up with accurate and practical financial projections; thus, it can be used as a valuable tool in the decision-making process, relying on the data in the business environment. This paper therefore examines the revolutionary potential of integrating deep learning technology into ERP systems to drive the next generation of financial analytics.*

Keywords: *ERP Systems, Financial Forecasting, Business Intelligence, Deep Learning, CNN-LSTM, Machine Learning, CSMAR Dataset, Predictive Analytics.*

I. INTRODUCTION

Digital transformation has altered how operations, competition and growth is carried out by modern organizations. Enterprise-wide digital infrastructure has increasingly been assuming a more of critical role with the adoption of automation, data analytics and cognitive systems in industries. It is no more a fact that businesses are simply accumulating information, they can work in real time to make an analysis of information and begin to draw insights that can be acted on and apply them to make any financial and strategy decision [1]. This has led to a feeling of desperation towards the need to be able to be ready to hand platforms that not only automate enterprise processes but also promote the ability to provide intelligent and data-driven forecasting and planning [2][3][4].

Enterprise Resource Planning (ERP) systems are usually seen as the digital core of modern organizations. These systems also provide built-in forums where key business processes are managed and coordinated [5], which comprise operations, supply chain, finance and human resources [6]. They are implemented to centralize information among the different departments so as to access the information in one location and make the working processes easier [7]. Nevertheless, ERP systems are also superior in capturing and storing transaction information, but they tend to lack the deep power that is associated with strategic decision-making [8]. In ERP situations, ERP tools have helped close such a gap by further integrating Business Intelligence (BI) [9], into mundane data to convert it into knowledge, in the form of reporting, visuals and predictive analytics. ERP convergence with BI has emerged as the convergence hot spot of the modern data-intensive enterprise, where informed and timely decision-making is required to remain competitive [10]. Specific financial decisions require the application of real-life knowledge and the right predictions. It is now unnecessary for business executives can possess forecasting programs that will merely provide them with hints of what has occurred in the past, but also forecasting programs that will become the case hereafter [11][12]. The demand to have complicated intelligence forecasting applications on the ERP systems is ever-increasing, with financial operations increasingly data-intensive [13].The foundation of business planning and risk management could be attributed to financial forecasting. In an ERP system, it helps an organization to predict their earnings and approximate their cost, cash flow and how to utilize their resources in a better way to plan. Rapid response to the market shifts and strategic decisions that can be made based on data demand appropriate forecasting [14]. Nonlinear trends, large dimensions and time fluctuations in the financial data development as it is the case with big data, however, cannot be addressed with the current forecasting models (ARIMA model, linear regression, and exponential smoothing). It is then based on the assumptions that cannot be true in the real life limiting its application in dynamic and fluctuated markets.

Machine learning (ML) [15] has been proposed as a revolutionary solution to the field of financial forecasting to deal with these deficits. Compared to the conventional statistical methods [16], ML models are dynamic, data-driven and have the ability to detect a latent structure in high-dimensional data. They are good at gauging nonlinear relationships, multivariate information and learning of past trends to predict the future. This renders ML [17] a perfect methodology to improve the degree of examination of the ERP-unified BI systems [18].Deep Learning (DL) has demonstrated itself as a potent field, especially in cases where there are large volumes of unstructured time-related information. DL models refer to approaches that use artificial neural networks and are able to extract features in an automatic fashion based on the hierarchy. This does away with hand-coding feature engineering, as in most conventional models. It was found that all CNN and LSTM network-based, and spatio-temporal methods were helpful in the learning of the spatio-temporal patterns and long-term temporal correlations, respectively. DL models are able to interact with complicated relations and generate high-accuracy projections when subjected to financial complications [19]. It is their ability to perform nonlinear modeling, adapt to time dynamics, and scale to the volumes that modern financial analytics is concerned with. An alliance of sophisticated ML and, more precisely, DL a significant step in that direction [20]. It is a move to a smarter enterprise that goes way beyond just processing data; systems that actually take action on their data to learn, make predictions, and contribute to informed financial decision-making on a mass scale.

A. Motivation and Contribution of the Paper

The rationale of this research is that in the current enterprise resource planning (ERP) systems, the need to have appropriate and intelligent financial forecasting systems is increasing. As the monetary markets become increasingly dynamic and increasingly complex, many traditional forecasting models have a hard time keeping up with the nonlinearities and time dependence that may be unveiled using the large amounts of financial information. Moreover, ERP systems generate and process a high level of financial data, most of which cannot be used in predictive analytics. The present study employs a DL framework and proposes a CNN-LSTM hybrid model to enhance the predictive analytics of financial forecasts based on the CSMAR data. The model can facilitate more informed and expedient financial decision-making by identifying spatial features and considering temporal dependencies. This can be explained by the main contributions of this research as follows:

- Applied CSMAR financial data to simulate real-world financial forecasting problems by considering an ERP scenario.
- Performed comprehensive preprocessing of data such as data cleaning, dimensionality reduction, data normalization in order to supply quality inputs into the model.
- Divided the dataset into separate training and testing sets so that it can make intense training of the model and their assessment performance.
- Developed and trained a hybrid CNN-LSTM architecture to absorb an optimal amount of feature-level structure and temporal behavior of the financial time-series data.
- Evaluated model-performance with typical statistical parameters like R^2, RMSE, MAE, and MSE in order to ascertain reliability of forecasts.
- Providing useful information to ERP-based BI systems while guaranteeing the model's efficacy in raising the quality of financial forecasts.

B. Justification and Novelty of the Paper

The research is notable because it uses a hybrid model of a deep learning approach to improve the fidelity of a financial forecast in ERP systems. The study also overcomes the drawbacks of the old methods of forecasting because they adopt the nature of nonlinear and temporal financial data that could not be considered in the previous methods. The resource commitment ought to be rationalized by adequate forecasting, in order to gain even more control over cash flow, effective assistance in the strategic financial decision-making. Intelligent and data-driven models added to the enterprise system as such will fill an encouraging void in the analytical functions of the ERP, and thus support its strengths in the area of real-time decision-making. Such an impressive success of the model is also evidence of its ability to transform into one of the key elements of the new generation of ERP modules, as not only does the model help enterprises adapt to the changes in the market swiftly but also avoid financial threats.

C. Structure of Paper

The structure of the paper is presented as follows: Section II discusses the previous research on enterprise resource planning (ERP) financial forecasting using the assistance of BI and ML. Section III explains how data have been collected, prepared to undergo analysis, run through the ML models and their performance evaluated. Section IV involves the analysis of the performance of models and experiment results. Lastly, V displays the most valuable findings and offers the prospects of further research.

II. LITERATURE REVIEW

In this section, the latest advancements in ML-based forecasting of ERP financial systems are summarized, with a special emphasis on DL models that enhance predictability, maintain business intelligence, and facilitate timely healthcare decisions in a dynamic business environment. Some of the works which have been reviewed are:

Table 1 : Summary of Existing Literature on Ml Applications in ERP-Based Financial Forecasting

Author(s)	Methodology	Dataset	Key Findings	Limitations	Future Direction
Jain& Kulkarni (2023)	AI techniques using historical financial data; conceptual & case study approach	Financial data	AI improves forecasting accuracy, budgeting efficiency, and supports dynamic financial strategies	No ERP system integration; lacks ML model comparison; limited BI discussion	Incorporate AI forecasting into ERP systems with BI dashboards for real-time business planning
Tewari (2023)	Comparative analysis of ML techniques (DL, RL, time series) vs. statistical models	Real-world financial market data	ML models outperform traditional methods in accuracy, speed, and decision support	No ERP or BI framework; lacks specific ERP application context	Apply hybrid ML models within ERP systems; integrate forecasting into enterprise BI tools
Zhang (2022)	Deep learning with TCN-LSTM model; optimization algorithms	ERP-based financial datasets	Proposed DL model improves risk prediction accuracy and forecasting stability	Focus is on risk prediction, not comprehensive financial forecasting; limited model diversity	Extend analysis to financial forecasting models; integrate BI modules and real-time ERP analytics
Narne (2022)	AI/ML-based ERP automation framework using NLP, reinforcement learning, predictive analytics	Industry-wide ERP case studies	Enhanced process throughput (25%), reduced decision time (40%), improved resource use (15%)	General focus on ERP process optimization; lacks forecasting and ML model comparison	Apply proposed AI-ERP framework to financial forecasting use-cases with comparative model evaluation
Kunchala (2022)	Descriptive analysis of AI/ML in SAP FICO modules; real-time insights	SAP ERP systems	Improved automation, anomaly detection, cost optimization in SAP finance	No empirical ML model testing; lacks comparative or quantitative forecasting results	Incorporate empirical ML benchmarking and forecasting metrics into SAP ERP modules
Perumallaplli (2021)	Models for supervised and unsupervised ML used in fraud detection and financial forecasting	SAP ERP financial datasets	Improved fraud detection, forecasting accuracy, and compliance through ML models	Focused more on fraud detection than forecasting performance comparison	Expand model scope to include forecasting accuracy, processing time, and BI integration

Jain and Kulkarni (2023) identify the massive participation of AI in the financial practice. It assumes that AI-based forecasting and budgeting may react to the market forces, optimize resource distribution and enable quick adjustments. The paper also addresses the use of AI to enhance operational efficiency and crisis decision-making. It acknowledges the problems related to computational complexity and interpretability, and establishes connections between artificial intelligence and financial practice through case studies. These two factors (AI and financial practices) are concluded with the help of certain informative case studies, and all of them lead to the strength of AI in streamlining the operations and making decisions more efficient and strategic [21].

Tewari (2023) discusses how ML has been used in forecasting models of the financial market and compares it to conventional statistical methods. Evaluating the predictive efficacy of AI-driven models over financial trends, risk management, and decision support within a corporation, the study employs deep learning, time series forecasting, and reinforcement learning. The research concludes that the AI-based models are more efficient compared to the conventional forecasting engines concerning complex data where humans can supervise minimally. The article contributes to reveal the necessity to improve the data bias, regulatory compliance, and ethical issues to exploit the potential of AI in financial predictions fully [22]

Zhang (2022) ERP, or enterprise resource planning, is defined and introduced in this article. Next up is a DL-based algorithm for predicting financial risk. The strategy involves training the parameters of a deep learning model with an algorithm and a specific design for temporal convolutional networks network architecture for long and short term memory (TCN_LSTM). Finally, various benchmark models and evaluation approaches from comparative research are utilized. Prediction outcomes are more stable and accurate when derived from a risk prediction model that uses deep learning. Using this proposed methodology, they can help businesses better use their limited resources, improve their resource planning, and ultimately increase their bottom line [23]

Narne (2022) discusses AI and ML technology in automation and optimization of ERP systems. It employs such technologies as predictive analytics, NL processing, and reinforcement learning to automate repetitive activities, enhance forecasting accuracy and optimize resource usage. The suggested AI-ML-enhanced ERP platform has three fundamental layers: data transformation, smart analysis and decision support. Research indicates sharp increases in all the industries, like a 25% improved process throughput, a 40% decrease on decision-making time, and 15% improvement towards the use of resources. Other challenges such as cost of implementation and data privacy are debated [24]

Kunchala (2022) The incorporation of AI and ML in the SAP Finance and Management Accounting (FICO) modules makes the SAP system efficient and smart, as discussed in this paper. The adoption of automation, predictive analytics, anomaly detection, or cost-optimizing are brought into the fore in the paper to bring about a transition of smarter financial operations in contemporary businesses. This mix of the technologies is bringing about changes such as the trend towards smarter financial processes in contemporary organizations [25]

Perumallaplli (2021) The paper discusses how machine learning techniques can be incorporated in SAP ERP systems to perform predictive finance management. The research would enhance the analysis of anomaly, fraud prevention, and forecasting of financial results in real-time by using ML models. The network enables identification of anomalies through the use of supervised learning and fraud detection through unsupervised models thereby increasing efficiency and accuracy regarding the financial management procedures. The outcomes demonstrate that there are massive changes in the number of violations that can be identified concerning compliance, fraud-related activities, and financial predictions (in comparison with traditional ERP systems). The proposed solution presents operational suggestions to organizations [26]

Table I summarizes the existing literature on machine learning (ML) financial forecasting within the ERP system. It highlights the deep-learning methods used, the most important findings and limitations, and potential areas for future research, such as the accuracy of the forecasts, trends over time, and the results' practical enterprise applicability

III. METHODOLOGY

The research methodology follows a systematic process to establish an effective machine learning model for predicting financials, as illustrated in The process starts by obtaining financial data from the CSMAR database, which has been commonly common in empirical finance research. This raw data passes through an extensive data preparation stage, which involves 3 major steps; data cleaning, where the records in the data are cleaned up to remove inconsistencies and missing values, normalization, where the data range is standardized and dimensionality reduction, where redundant or useless features are removed to make the model more efficient. The data is then split into training and testing data after preprocessing in order to facilitate the successful training and validation of the model. A hybrid CNN-LSTM model is then implemented with the purpose to learn spatial and temporal patterns of financial data. The convolutional layers acquire meaningful features, and the LSTM ones acquire time dependencies. Measures of behavior that are used and thus defined as metric measures of model behavior include R^2, RMSE, MAE and mean square error (MSE). The methodology facilitates the creation of meaningful and sound financial projections within an ERP-based business intelligence platform.

A. Data Collection

Financial forecasting and decision assistance systems that leverage machine learning and big data are the primary focus of this research. To achieve this goal, the study first analyses financial data from Chinese A-share listed businesses, which are stored in the CSMAR database. This data set encompasses the fundamental financial metrics of all A-share listed corporations spanning the years 2000–2023. Financial metrics such as total assets, net profit, revenue growth rate, debt-to-asset ratio, market value, and R&D expenses amount to 54,389 observations. In addition to facilitating the creation and testing of different financial forecasting models, this data offers a robust empirical basis for the research. Here are the data visualizations:

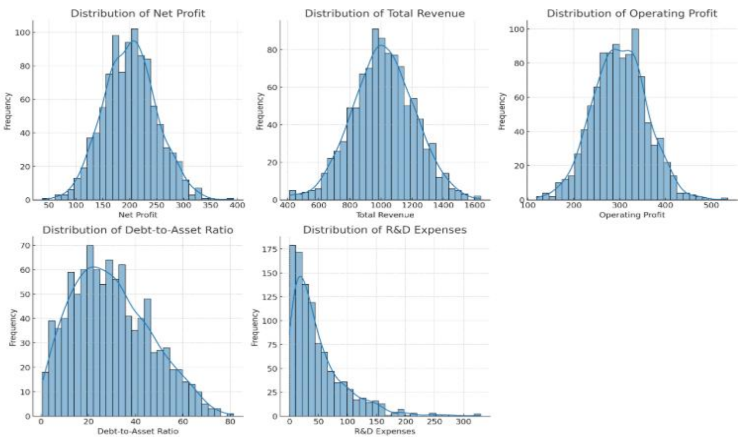

Figure 1 : Distribution of Key Financial Indicators in Dataset

The distribution of key financial indicators is illustrated in Figure 1 by a series of five histograms. The top row shows distributions for Net Profit, Total Revenue, and Operating Profit, all of which approximate a normal distribution. Net Profit is centered around 200, Total Revenue around 1000, and Operating Profit around 300. In the bottom row, the distribution for Debt-to-Asset Ratio also appears somewhat normal, peaking around 20. However, the distribution for R&D Expenses is highly skewed to the right, with most companies having low expenses and a few having very high expenses.

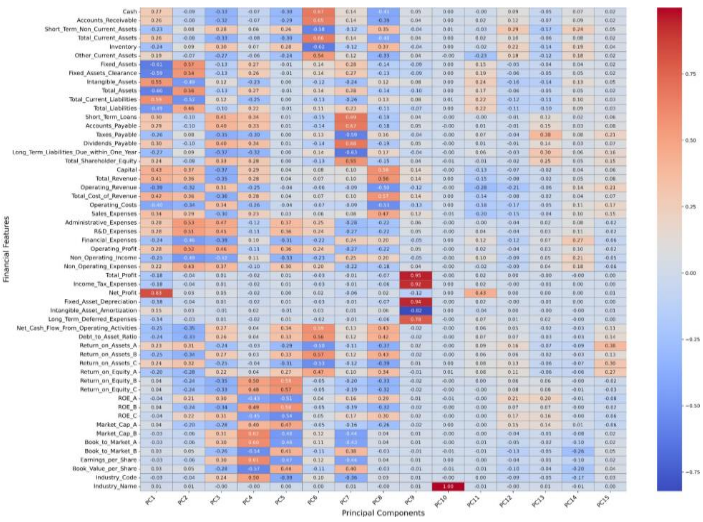

Figure 2: Correlation Heatmap of the Dataset

This is a correlation heatmap that visualizes the relationship between financial features and principal components (PC) in Figure 2. The x-axis represents the principal components, labeled PC1 through PC15, while the y-axis lists various financial features such as 'Cash', 'Total Assets', 'Total Liabilities', and different 'Return on Equity' metrics. The direction and intensity of the link are shown by the colour of each cell. A strong positive association is indicated by red shades, a strong negative correlation by blue shades, and a weak or non-existent correlation by lighter colours, especially white and light blue/red. The correlation values, which can range from around -0.75 to +0.75, are displayed on a colour bar on the right.

B. Data Preparation

The dataset must undergo comprehensive pre-processing to ensure data quality and consistency, which are essential for accurate financial time series forecasting. Improper or noisy data can lead to misleading patterns and reduce model effectiveness. To enhance reliability and performance, the following pre-processing steps were performed:

C. Data Cleaning

Data cleaning refers to the process of locating, identifying, and either fixing or removing erroneous, incomplete, inconsistent, or irrelevant information in order to make a dataset correct, trustworthy and allegedly analyze or train a model. This is one of the essential processes to perfect the quality of data and performance and generalization of machine learning models. The study undertook the following steps as part of data cleaning exercise in the study:

- Elimination of duplicate or unreliable data to provide continuity and reliability in terms of data over the time series.
- Blank fields in the essential financial indicators were filled with industry median values in order to create uniformity without creating bias.
- Standard deviation and box plots were used to detect and correct outliers, which was used to make sure that extreme values did not distort the statistical integrity of the data set.

D. Normalization

Normalization is a kind of data pre-processing technique that makes numerical features use a common scale without causing distortions in meaning due to the differences in ranges of values. It makes sure that a single feature would not be prevailing due to its magnitudes and that each feature would participate in proportionate levels of model training [27]. Z-score normalization (also called standardization) is a method of transforming data in order to make feature values have a mean of 0 and a standard deviation of 1. The transformation is performed using Equation (1):

$$Z = \frac{X-\mu}{\sigma} \quad ⟦$$

where X represents the initial data point, μ denotes the feature's mean, and σ denotes the feature's standard deviation, respectively.

E. Dimensionality Reduction

Dimensionality reduction, or shrinking the feature space while retaining the key information, is an essential step in preparing high-dimensional datasets for machine learning. Principal Component Analysis (PCA) was used in this study to deal with dataset noise, multicollinearity, and redundancy [28]. By using a linear transformation, principal component analysis (PCA) separates the initially connected variables into a new set of independent variables. The rank these variables according to the amount of data variance they explain. Later, PCA was used on the dataset to get the main components. Formulated in Equation (2) PCA tries to discover a projection matrix W that changes the original dataset X into a model with fewer dimensions Z:

$$Z = X.W \qquad (2)$$

Here, $X \in \mathbb{R}^{n\times p}$represents the standardized data with n observations and p features, $W \in \mathbb{R}^{p\times k}$ is the matrix of eigenvectors.

F. Data Splitting

Data splitting is an important part of machine learning for checking how well a model works. The dataset was divided into 70% for training and 30% for testing to ensure there was 00.

G. Proposed Approach: A CNN-LSTM Hybrid Architecture

CNN-LSTM combines CNN feature retrieval with LSTM sequence guessing capabilities. The CNN-LSTM is commonly used for image and video tagging and activity identification. When combined, they alleviate two prevalent issues: visual time series forecasting and the creation of text annotations from picture sequences. In the first stage, CNN layers are used to perform convolution operations over the input data, identifying local and spatially correlated patterns across features[29]. The convolution operation at time step t for the k-th filter is defined in Equation (3):

$$Z_t^{(k)} = \sigma(\textstyle\sum_{i=0}^{n}\sum_{j=0}^{m} W_{i,j}^{(k)} X_t + b^{(k)}) \qquad (3)$$

The ReLU activation function is denoted by σ(·), the input feature matrix is represented by X, and the output of the convolution at time t is denoted as $Z_t^{(k)}$. After the convolutional layers, the feature maps are flattened to make them one-dimensional sequences. These sequences are then inputted into the LSTM network. The LSTM module models the temporal dynamics in the data using gated memory units that manage the flow of information over time [30]. The key computations in an LSTM cell are as follows:

The forget gate determines the relevance of previous information by deciding whether to retain or discard it. It outputs f_t, which ranges from 0 to 1, where 0 means complete discarding and 1 indicates full retention. The calculation for the forget gate is shown in Equation (4).

$$f_t = \sigma\left(W_f . [h_{t-1}, x_t] + b_f\right) \quad (4)$$

Similarly, the input gate processes the current input (x_t) and the prior output (h_{t-1}) to determine which new values should be changed. It uses a weight matrix W_i, a sigmoid function σ, and a bias term b_i, generating a candidate value for the current cell state $\hat{C}_t$ as displayed in Equation (5):

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i) \quad (5)$$

The candidate cell state value $\hat{C}_t$ is calculated using the hyperbolic tangent function as shown in Equation (6)

$$\hat{C}_t = tanh(W_c . [h_{t-1}, x_t] + b_c)(6)$$

The updated cell state C_t combines the forget gate output f_t, the previous cell state C_{t-1}, the input gate output i_t, and the new candidate state $\hat{C}_t$ as displayed in Equation (7):

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (7)$$

The current output is then adjusted by the output gate based on the cell condition. Applying the hyperbolic tangent function to the current cell state and scaling it by the output gate value depicted in Equations (8) to (9) yields the final output h_t, while a sigmoid function is used to calculate the output o_t:

$$o_t = \sigma(W_o . [h_{t-1}, x_t] + b_o) \quad (8)$$
$$h_t = o_t * \tanh(C_t) \quad (9)$$

This hybrid architecture significantly improves the model's ability to learn complex, nonlinear dependencies in financial data, yielding more accurate forecasts compared to traditional statistical or single-model deep learning approaches. The architecture is visually represented in Figure 4:

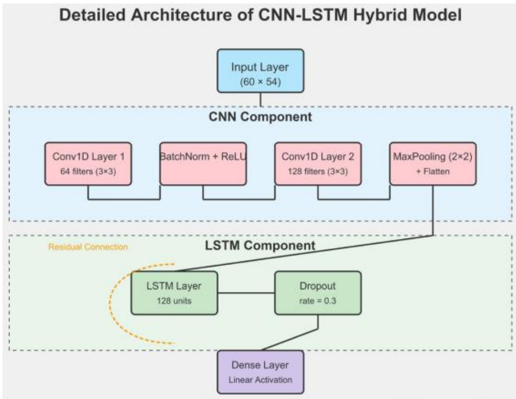

Figure 3 : Architecture of the CNN-LSTM Model

H. Evaluation Parameters

This section details the primary metrics used to evaluate regression model performance, offering quantitative measures to assess their accuracy, reliability, and overall effectiveness in various predictive tasks:

a) Mean Absolute Error (MAE)

Absolute error is the sum of all foresee errors. Taking a mean of all absolute errors yields the medium absolute error. Presentation 10 is the mathematical formula:

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

b) Mean Squared Error (MSE)

The MSE is a popular evaluation measure used for regression whereby the averages of the squared representations of the true values and the values that have been forecasted are calculated. It measures the magnitude of error with regard to the predictions of a model. In Equation (11) one can calculate MSE:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

c) Root Mean Squared Error (RMSE)

RMSE is a popular statistical metric for assessing a model's quality. Equation (12) gives its mathematical expression, which is the square root of the mean of the squared deviation of the anticipated value around its preliminary condition. See below for the given expression.

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

d) Coefficient of Determination (R-square)

It is the most significant measure of model certainty in the data, which is required in any description of regression models. The value of the coefficient of determination take up values between 0 and 1. The more a value is, the more reliable a model. Calculation of R-square can be expressed as given below in Equation (13) as follows:

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

Collectively, these metrics of evaluation provide an in-depth assessment of predictive ability of the model.

IV. RESULTS ANALYSIS AND DISCUSSIONS

Advanced machine learning methods incorporated within ERP systems are shaking the financial prediction and business intelligence arenas. The paper offers an exploratory comparison of deep learning model in an ERP environment in terms of its predictive accuracy targeted at financial decision making. Python with TensorFlow and Keras frameworks were utilized in all the experiments on an enterprise-grade computing infrastructure with operating system 64-bit Windows Server OS, 64 GB of RAM, which is configured to address the use on large-scale ERP analytics. The CNN-LSTM network was identified as one of the high-performing architectures that could be used to predict the dependent variable (Table II), with $R^2$0.92; RMSE 0.052; MAE 0.036; and MSE 0.0027. These findings show the usefulness of the model to provide effective financial forecasts and catching non-linear temporal relationships. The results highlight the possibility of CNN-LSTM models to drive intelligent ERP modules through which an organization can obtain viable insights and devise strategic plans.

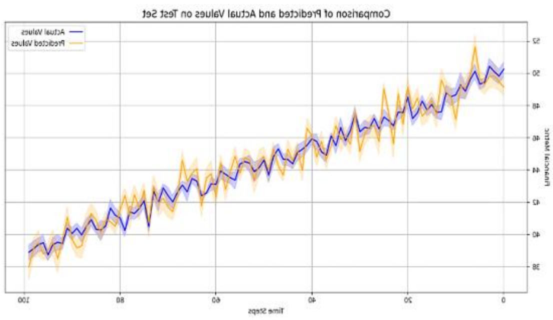

Figure 4 : Comparison of Predicted and Actual Values for the CNN-LSTM Model on the Test Set

The graph of Figure 4 shows regression analysis of proposed model. x axis This is the Time Steps, with a range of 0 to 100 and y-axis is a Financial Metric, with a range of 38 to 52. Two lines are plotted: a blue line for "Actual Values" and an orange line for "Predicted Values." The graph shows a general downward trend for both sets of values over time. Shaded bands, light blue and light orange, surround each line, representing confidence intervals. The predicted values track the actual values quite closely, with the confidence intervals of the two lines largely overlapping throughout the depicted period.

Table 2 : Evaluation Results of CNN-LSTM for Financial Forecasting in ERP Environments

Parameter	CNN-LSTM
R^2	0.92
RMSE	0.052
MAE	0.036
MSE	0.0027

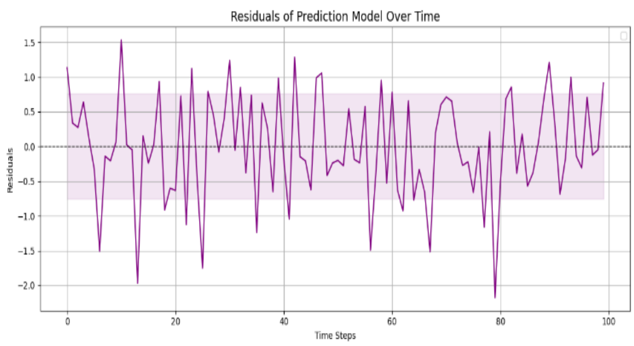

Figure 5 : Residuals of Prediction Model over Time

The residual plot showcases the model predictions over time in the Figure 5. The x-axis is labeled "Time Steps," ranging from 0 to 100. The y-axis is labeled "Residuals," spanning from -2.0 to 1.5. A purple line plots the residuals, which are the differences between predicted and actual values. The line fluctuates around the zero-residual line, which is represented by a dashed gray horizontal line at y=0. A light purple shaded band highlights the range of residuals between approximately -0.75 and 0.75. The graph shows that the residuals are more or less centered around zero although few cases could be found where the values are not within the shaded band.

A. Comparative Analysis

The section compares the machine learning models of financial forecasting in ERP systems by using Mean Absolute Error (MAE) as the evaluation metric. The CNN-LSTM model demonstrated the best MAE of 0.036 as indicated in Table III, as it has the best forecasting accuracy since it can grasp both spatial and temporal patterns. The LSTM model achieved an MAE of 11.64, with good sequential learning capacities but with less precision than the CNN-LSTM hybrid. The MAE of the Random Forest (RF) model was the worst (19.79) which could be considered as bad capability to address the time dependencies. The findings indicate that CNN-LSTM has the potential to become the most effective model to apply in achieving efficient financial forecasting in ERP-based business intelligence systems which is a good opportunity to enhance strategic financial decision-making.

Table 3 : Comparison of Machine Learning Models' Performance for Financial Forecasting in ERP Systems

Models	MAE
RF[31]	19.79
LSTM[32]	11.64
CNN-LSTM	0.036

The implementation of advanced models of DL in the financial forecasting of the ERP has resulted in the emergence of new opportunities to enhance the accuracy of the predictions and the decision-making. Among them, the hybrid CNN-LSTM model proved to be the most successful and more effective than simpler ML and the baseline DL models in the task of explaining the more complex trends of the financial time series data. CNN-LSTM model works to the advantage of convolutional layer to extract features and LSTM unit to perform sequential learning. It is this dual capability that enabled the model to give greater consistency and accuracy of the forecasting results. When compared with other models such as the Random Forest and the ordinary LSTM, the CNN-LSTM outperformed in performance and stability. Such a combination of flexibility and precision can be seen as an appealing alternative to approach financial forecasting task in ERP systems and can provide data-driven strategies and more responsive financial management.

V. CONCLUSION AND FUTURE WORK

The predictive capacity of ERP systems is also becoming a more significant issue, as companies are increasingly interested in being actively involved in responding to financial risk and complexity. The paper presents a CNN-LSTM DL architecture scaled to the requirements of financial forecasting in the ERP setting, showing apparent advantages over the outdated methods. After extensively testing the CSMAR, the model was found to be highly accurate, with an R^2 of 0.92 and a MAE of just 0.036, indicating that it can effectively learn complex financial patterns and relationships. The integration of convolutional and recurrent neural components has enabled the system to effectively consider both the space- and time-varying attributes of financial data, resulting in more consistent and dependable predictions. The hybrid CNN-LSTM architecture was superior to standalone LSTM and random forest in all important metrics. Despite the strengths, the model can be applied to a single dataset and a controlled environment.

Future studies should aim to generalize the model to diverse datasets and real-time enterprise systems. In addition, explainable AI approaches, adaptive learning algorithms, and support for real-time streaming data may enhance transparency, scalability, and responsiveness. The directions earmarked in these futures are those of making the system firmer, readable and compatible with the actual-world applications of ERP.

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