JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES
www.journalimcms.org

ISSN (Online) : 2454 -7190 Vol.-21, No.-03, March (2026) pp 134-152 ISSN (Print) 0973-8975

DESIGNING AN AUTOMATED DENSE BI-LSTM-AIDED FRAMEWORK FOR ENHANCING THE PERFORMANCE MANAGEMENT IN BUSINESS ORGANIZATION USING CROSS ATTENTION-BASED FEATURE FUSION

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https://doi.org/10.26782/jmcms.2026.03.00010

(Received: December 25, 2025; Revised: February 20, 2026; Accepted: March 08, 2026)

Abstract

The role of management is to evaluate and validate the objectives of an organization. The management's role in state-owned business enterprises is more critical due to the influence of the existing human resource performance management system. The organization's intelligence helps to gather important data from the large unstructured data and modifies it into useful data to improve the efficiency and productivity of the organization. In the era of the Internet, conventional performance management struggled to meet the modern development of an enterprise. Hence, organizations must continuously innovate and improve their performance management strategies. Deep learning has shown potential in enhancing business intelligence with the automated validation of large and complex data sources. Nevertheless, it has not achieved much attention as they are not efficient in decision making process within the organization. Therefore, in this article, an advanced deep learning-based network is designed for effective decision-making to enhance the growth of a business organization. Initially, the necessary data for the analysis is taken from the available resources. Subsequently, the significant features from the data are extracted using the T-distributed Stochastic Neighbor Embedding (T-SNE), Principal Component Analysis (PCA) and statistical features. The extracted features are combined using the Cross Attention-based Feature Fusion (CAFF). In the end, the resultant fused features are given to Dense Bidirectional Long Short-Term Memory (D-BiLSTM) for performing efficient decision-making. Finally, comparative analysis is conducted to validate the functionality of the model. The result demonstrates that the designed framework is more efficient in decision-making to enhance the productivity of business organizations.

Keywords: Performance Management, Business Organization, T-distributed Stochastic Neighbor Embedding, Cross Attention-based Feature Fusion, Dense Bidirectional Long Short-Term Memory

I. Introduction

The extensive and continuous integration of the Internet model within organizations had a large impact on the overall organization's development, and it has increased the marketing competition [XIX]. In recent days, most organizations do not perform market invasion and expansion without careful strategic evaluation. For the rapid implementation of Internet-based organization models, maintaining organizational sustainability and operational stability is important [VIII]. The organization must pay attention to the total quality and the capacity of the internal employees in the internal performance management, rather than only considering the organization's size [I]. In the internet era, organizations include modern technologies in their performance management to support the organization's improvement in all aspects.

The performance management models describe operational frameworks to guide organizational activities toward predefined objectives [XV]. Most importantly, the organizations handles different strategies, systems, operations and networks employed by the organizations for representing the goals and objectives reported by the management for supporting the strategic operation and the current management via evaluation, measurement, planning, rewarding, control and handling the functionality and for supporting the organizational change and learning [III]. Different experiments have been performed to explain the importance of performance management approaches in the current business environment [XII]. As changes arise from uncertain and unpredictable conditions, managing the problems in a business organization is useful to enhance the business growth [XXI].

In conventional organization management models, most of the workflow is handled by manual steps that lead to inefficiencies and unpredictability in overall enterprise operations [X]. Initially, the entire manual management process does not improve the performance of management. In addition, manual management requires a huge amount of financial investment that increases the management costs. But, due to the human errors and inconsistencies, management mistakes frequently occur and result in various challenges for the organization [XVIII]. One of the primary problems encountered in organizations is managing the huge amount of data. Therefore, business intelligence mechanisms have been employed for handling the huge volume of data with the help of deep learning. The accuracy of business performance predictions is increased with the help of deep learning techniques [XVI]. By employing deep learning strategies to handle the business details, organizations can obtain better insights into their tasks and make highly informed decisions. Therefore, a deep learning model is employed in this work for predicting the performance of business organizations.

The important contributions of the recommended performance management model are given below.

- To implement a new method for performance management in business organizations is developed. This model analyzes the performance of a management without human involvement and provides subjective decision-making for enhancing business growth. Moreover, this automated system improves prediction accuracy and helps in achieving the overall goal of the business organization.
- To suggest a CAFF for fusing the features obtained from t-SNE, PCA, and statistical features. The designed CAFF efficiently integrates the complementary data from distinct features that are useful in improving the model's robustness, and accuracy. The relationships between heterogeneous features are efficiently captured and preserved by the CAFF mechanism.
- To present a D-BiLSTM technique for decision-making and productivity prediction in a business organization. This technique captures long-range dependencies using the Bi-LSTM model. The dense connections present in the network are capable of handling complex patterns in data that results in more accurate performance insights and predictions.

The organization of this designed model is given as follows. The traditional performance management strategies in business organizations are detailed in Section II. The effective feature extraction and fusion process in the developed framework for performance management in business organizations are explained in Section III. An automated productivity prediction model for performance management in business organizations using D-BiLSTM is demonstrated in Section IV. The results and their related discussions are shown in Section V. The summary of the automated network is provided in Section VI.

II. Existing Works

Related Works

In 2021, Machireddy et al. [IX] have presented an approach using machine learning to handle the business successfully. Further, the responsibility of the system was to analyze the infrastructure and helping them to enhance their performance. Moreover, the performance of this work was analyzed among other techniques to demonstrate its efficiency in business sectors.

In 2023, Gholami et al. [XVII] have explored the efficacy of deep learning in improving business intelligence for managing organizations. The model's F1 score and accuracy were estimated over the traditional approaches. The designed deep learning strategy classified the feedback of the customer into negative and positive sentiments. This work highlighted the potential of the designed framework over other techniques.

In 2025, Sun [XXIII] has investigated the organization's performance using deep learning. At first, the data was normalized and pre-processed. Further, the index selection was carried out. This work considered the 1D CNN techniques for forecasting the functionality of the organization. The model achieved higher accuracy in the validation of customer satisfaction.

In 2022, Luo [II] has analyzed the issues present in the present performance management models and concentrated on offering support for the management to improve their performance. According to the RNN technique, this work recommended an organization network with a path optimization model.

In 2024, Visani et al. [VI] have implemented an action research model using machine learning to analyze the complexity of improving a business. This work evaluated the business analytics role in the sector of business management and offered insights for developing a machine learning-assisted performance management approach.

Research Gaps and Challenges

In a business organization, performance management is a strategic and continuous operation that aligns individual employee objectives with the overall business goals, resulting in enhanced productivity as well as employee management. Although performance management is a crucial research topic, a very limited amount of work analyzed this topic. The conventional model has the following research challenges.

- The existing models fail to capture the complex relationships among the data that reduce the accuracy of prediction. Therefore, to properly extract the complex and related features, an effective feature extraction operation is required.
- Some traditional techniques often demand manual interventions for predicting performance management, which results in errors and subjective outcomes. Therefore, developing an automated framework for performance management is significant.
- Some of the deep learning-assisted models struggle to handle large datasets and they showcase slow performance. Therefore, developing a model that can handle large datasets and provide better results is important.

To rectify these concerns, this work suggests a new performance management approach in business organizations. Table I lists some of the conventional performance management model's features and complexities.

Table 1. Features and challenges of traditional performance management models in business organization

Author [citation]	Methodology	Features	Challenges
Machireddy*et al.* [IX]	Reinforcement Learning	• It can adapt to changing environments and learns without human intervention. • It tackles the complex problems in business organization and enhances productivity.	• It demands vast amounts of data and takes more time for training. • Its computational cost is high and has low interpretability.
Gholami *et al.* [XVII]	CNN	• It automates the performance	• It demands more computational power

		monitoring and learns the features automatically. • It forecasts future performance trends on the basis of data patterns.	and time. • It requires proper regularization approaches.
Sun [XXIII]	1D CNN	• It is capable of handling high-dimensional data. • It allows quick recognition and decision-making.	• It often demands large data sources for high accuracy. • It is prone to overfittingissues.
Luo [II]	RNN	• It processes input data with various lengths. • Its accuracy rate is high and efficiently models the time series data.	• It faces the gradient issues andit is computationally intensive. • The training process is complex.
Visani*et al.* [VI]	Decision Tree	• It improves the efficiency of decision making. • It recognizes the new trends and patterns efficiently.	• It can't properly handle the missing values. • It struggles to handle the complex relationships.

III. An Effective Feature Extraction and Fusion Process in Developed Framework for Performance Management in Business Organization

Data Collection Details

For the designed performance management approach in business organizations, the following dataset is used.

Dataset ("Productivity Prediction of Garment Employees"): The link "https://archive.ics.uci.edu/dataset/597/productivity+prediction+of+garment+employees", is supported for accessing this data source. Access date: 2025-04-26. From this data source, 1197 data records are utilized for the designed work, where 299 (25%) data records are taken for testing and 898 (75%) data records are utilized for training. This resource is a multi-variant data source, including the time series data for the business contexts.

The data garnered from this data source is considered as $B_m,\ here\ \ m = 1,2,3,\ldots,M$ and the total count of this data is M .

Feature Extraction Process

Feature extraction is the operation of converting the original data into a useful format. So, the machines can analyze and process the data. This operation is essential for enhancing the interpretability, efficiency, and performance of the deep learning approaches to handle the complex data sources more precisely. Therefore, this work included the feature extraction process for improving the designed model's efficiency. Here, the feature extraction operation is performed in three stages and the operations are explained as follows.

T-SNE [XIII]: This model utilizes the gathered data B_m as input. The t-SNE approach supports converting the high dimensional data to a lower dimension. The primary concept of this approach is two-fold. The initial phase is the SNE strategy that is applied to the data points as another projecting approach of the high-dimensional Euclidean distance between the data points into the conditional probability. The relation between two data points y_k *and* y_j is expressed by the conditional probability $Q_{k|j}$ as given in Eq. (1).

$$Q_{k|j} = \frac{\exp^{\frac{-\|y_j - y_k\|^2}{2\sigma_j^2}}}{\sum_{j\neq l} \exp^{\frac{-\|y_j - y_l\|^2}{2\sigma_j^2}}} \tag{1}$$

Here, the variance is specified as σ. Further, the probabilities are specified in the real feature space as given in Eq. (2).

$$Q_{j,k} = \frac{(Q_{j|k} + Q_{k|j})}{2m} \tag{2}$$

Here, the term m indicates the dimensions of the results collection. The t-SNE approach utilizes the input factor called "perplexity" and is indicated as the continuous estimation of a specific number of neighbors. It is formulated in Eq. (3).

$$Perp(Q_j) = 2^{I(Q_i)} \tag{3}$$

Here, the term $I(Q_i)$ indicates the Shannon entropy as estimated in Eq. (4) and Q_i is estimated in bits.

$$I(Q_i) = -\Sigma_k Q_{k|j} \log_2 Q_{k|j} \tag{4}$$

For eliminating the network congestion, the student t-distribution is leveraged by the t-SNE approach with a particular independence degree. The low dimension's probability is formulated in Eq. (5).

$$r_{jk} = \frac{\left(1 + \|n_j - n_k\|^2\right)^{-1}}{\Sigma_{j\neq k}\left(1 + \|n_j - n_k\|^2\right)^{-1}} \tag{5}$$

Further, the t-SNE approach discovers the ways to outline the input data into a low dimension as n_j by estimating the divergence and to attain this, t-SNE leveraged a gradient-aided model. Thus, from the t-SNE, the significant features are extracted and the resultant features are specified as B_m^{F1}.

PCA [XI]: It is a feature extraction strategy that produces new features, and they are considered as the initial features' linear integration. This model employs the garnered data B_m as input. The PCA is expressed in Eq. (6).

$$PC_j = v_1 R_1 + v_2 R_2 + \ldots. + v_f R_f \tag{6}$$

Here, the principal component j is indicated as PC_j and the real feature k is R_k. Further, the numerical coefficient for the term R_k is given as v_k.

Thus, from PCA, the significant features are fetched, and the resultant features are specified as B_m^{F2}.

Statistical features [V]: From the gathered data B_m, the statistical features are extracted and are explained below.

(1) *Max:* It is leveraged to recognize the largest value in the given data and is shown in Eq. (7).

$$\max(B_m) \tag{7}$$

(2) *Min:* It recognizes the smallest value in a given data set and is shown in Eq. (8).

$$\min(B_m) \tag{8}$$

(3) *Mean* μ *:* It is drawn out on the basis of input data and the number of data points in a given dataset. It is shown in Eq. (9).

$$\mu = \frac{\sum_{m=1}^{M} B_m}{M} \tag{9}$$

Here, the total number of data is specified as M.

(4) *Median:* It is the given data's middle score and is estimated in Eq. (10).

$$Median = \frac{M+1}{M} \tag{10}$$

(5) *Standard deviation* $stdn$ *:* It is the factor of data's dispersion from its average and is calculated in Eq. (11).

$$stdn = \frac{1}{M}\sqrt{\sum_{m=1}^{M}\left(I_m - I_{m-1} - \mu\right)^2} \tag{11}$$

Here, I_m is the interval in the collected data.

(6) *Variance* σ^2 *:* It is the mean of the squares of variations between the expected and the observed values. It is determined in Eq. (12).

$$\sigma^2 = \frac{\sum_{m=1}^{M}\left(B_m - \mu\right)^2}{M} \tag{12}$$

(7) *Kurtosis* ζ_2 *:* It defines the degree of tailedness in the real-valued random factor's probability distribution.

$$\zeta_2 = \frac{1}{M}\sum_{m=1}^{M}\left[\frac{B_m - \mu}{\sigma}\right]^4 - 3 \tag{13}$$

(8) *Skewness* ζ_1 *:* It is a factor of a probability distribution's asymmetry of a real-valued random variable about its average. It is calculated in Eq. (14).

$$\zeta_1 = \frac{1}{M}\sum_{m=1}^{M}\left[\frac{B_m - \mu}{\sigma}\right]^3 \tag{14}$$

(9) *Correlation coefficient* cc *:* It is expressed in Eq. (15).

$$cc = \frac{\Sigma\left(d_j - \bar{d}\right)\left(h_j - \bar{h}\right)}{\sqrt{\Sigma\left(d_j - \bar{d}\right)^2\left(h_j - \bar{h}\right)^2}} \tag{15}$$

Here, the values of the terms d *and* h in a given data are indicated as d_j *and* h_j. Also, the average values of the terms d *and* h are specified as $\bar{d}$ *and* $\bar{h}$.

Thus, the statistical features are extracted, and the resultant features are indicated as B_m^{F3}.

Cross Attention-based Feature Fusion

The feature fusion integrates the features from distinct features to generate a highly informative feature representation. This operation enhances the functionality of the deep learning approaches by improving their capacity to differentiate among distinct patterns or classes. Therefore, to improve the model functionality and reduce the redundant features, feature fusion is performed. For this operation, the CAFF is utilized. Here, the extracted feature sets, such as t-SNE B_m^{F1}, PCA B_m^{F2}, and statistical features B_m^{F3} are provided as input.

The CAFF [XIV] builds 2 efficient weight distribution approaches: weight maximization and addition methods. Initially, the coefficients of feature weight are estimated in the CAFF along vertical as well as horizontal directions. Further, to improve the feature, these two weight coefficients are added. Further, the huge weight coefficient is attained by employing the maximization mechanism. Lastly, the result of these two operations is attained via fusion. The expressions for estimating the addition as well as maximization of weights are shown in Eq. (16).

$$\begin{aligned} A_{io} &= \sum_{o=1}^{I_b}\frac{\exp\left(y_{io}\right)}{\sum_{p=1}^{I_b}\exp\left(y_{ip}\right)}, \\ add &= \left(A_1 + A_2\right), \\ \max &= \left(A_1, A_2\right) \end{aligned} \tag{16}$$

Further, the fusion operation of cross-attention is shown in Eq. (17).

$$CAFF = concatenate\left[A_1, A_2, add, \max\right] \tag{17}$$

Here, the vertical and horizontal attention methods' weight coefficients are provided as A_2 *and* A. The weight coefficients addition task is indicated as add, while the maximization task is indicated as $\max$.

Thus, by employing CAFF, the feature sets are fused and the resultant feature is indicated as B_m^{CAFF}. The diagrammatic view of the implemented CAFF process is shown in Fig.1.

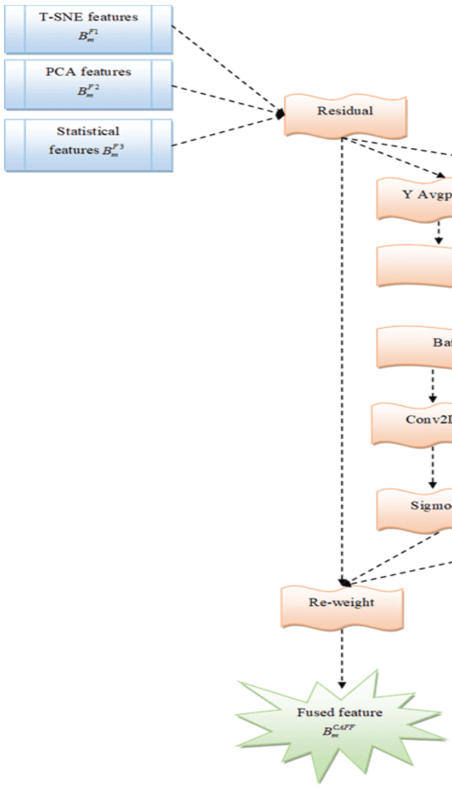


Fig.1. Diagrammatic view of the designed CAFF

IV. An Automated Productivity Prediction Framework for Performance Management in Business Organization using Dense Bi-LSTM

Suggested Dense Bi-LSTM for Prediction

Performance management approaches are significant in business organizations for enhancing their productivity and overall business outcomes. However, the traditional models fail to provide highly accurate results and also obtain limited performance when dealing with complex datasets. Therefore, this work presents D-BiLSTM for performance management in business organizations. Here, the D-BiLSTM utilizes the CAFF feature B_m^{CAFF} as input. The D-BiLSTM [XXII] integrates the densely connected layer with Bi-LSTM. It employs the merits of both kinds of layers: Bi-LSTM for capturing the temporal dependencies and processing the sequential data, and also the dense layers for feature extraction as well as non-linear transformations. Therefore, the D-BiLSTM is utilized in this work. The modules of D-BiLSTM are provided below.

Network inputs: The input of this technique is a variable-length data, which is specified as $B_m^{CAFF} = \{m_1, m_2, \ldots m_b\}$. Here, each word is indicated as a dense factor captured from the matrix of word embedding. Lastly, the word vector's sequence $\{e(m_1), e(m_2), \ldots e(m_b)\}$ is provided to the D-BiLSTM as input.

D-BiLSTM: It includes distinct Bi-LSTM layers. For the initial Bi-LSTM layer, the input is specified as a word vector sequence $\{e(m_1), e(m_2), \ldots e(m_b)\}$, and the outcome is $i^1 = \{i_1^1, i_2^1, \ldots, i_b^1\}$. Further, the input for the second Bi-LSTM layer is not a sequence $\{i_1^1, i_2^1, \ldots, i_b^1\}$, yet the fusion of the entire previous results is specified as $\{[e(m_1); i_1^1], [e(m_2); i_2^1], \ldots, [e(m_b); i_b^1]\}$, and the result is $i^2 = \{i_1^2, i_2^2, \ldots, i_b^2\}$. For the next (third) layer, whose input is $\{[e(m_1); i_1^1; i_1^2], [e(m_2); i_2^1; i_2^2], \ldots, [e(m_b); i_b^1; i_b^2]\}$ the same as the second layer. The subsequent layer performs similarly. The mentioned task is explained as follows.

$$i_v^s = \left[\overrightarrow{i_v^s}; \overleftarrow{i_v^s}\right], specially, i_v^0 = e(m_v) \tag{18}$$

$$\overrightarrow{i_v^s} = lstm\left(\overrightarrow{i_{v-1}^s}, G_v^{s-1}\right) \tag{19}$$

$$\overleftarrow{i_v^s} = lstm\left(\overleftarrow{i_{v+1}^s}, G_v^{s-1}\right) \tag{20}$$

$$G_v^{s-1} = \left[i_v^0; i_v^1; \ldots; i_v^{s-1}\right] \tag{21}$$

Average pooling: For a S layer D-BiLSTM, the result is $i^S = \{i_1^S, i_2^S, \ldots, i_n^S\}$. This module reads in and estimates the mean value of these factors; the estimation is derived as $i^* = average(i_1^S, i_2^S, \ldots, i_b^S)$.

Softmax layer: This phase is a simple softmax model that utilizes i^* as features and produces the predicted likelihood distribution over the entire data labels.

Thus, the D-BiLSTM predicts the productivity of the organization and enhances performance management through accurate decision-making. The pictorial representation of the D-BiLSTM-aided prediction process is shown in Fig.2.

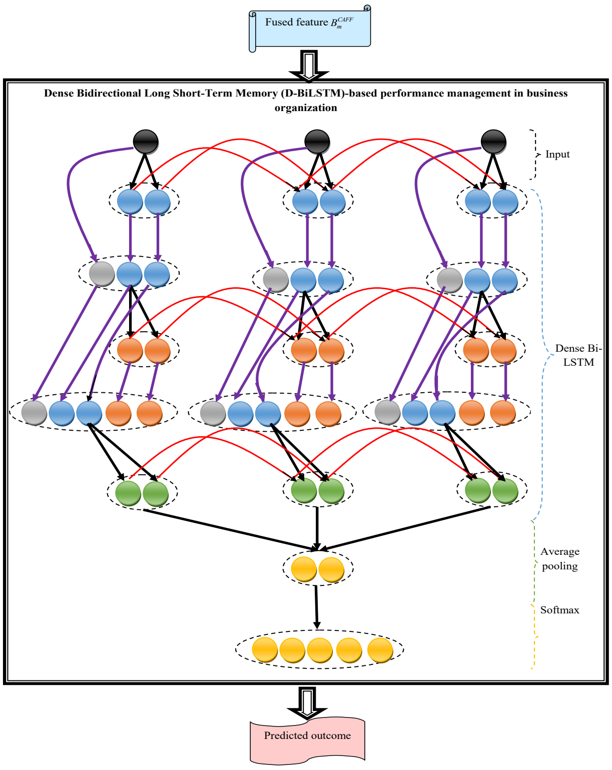


Fig. 2. Pictorial representation of D-BiLSTM-aided prediction for business organization

Structural View of Proposed Work

Performance management is a factor that supports the manager's observation and estimates the work of an employee. The objective of performance management is to generate an environment where individuals can perform to the best of their capacities and in alignment with the overall goal of the organization. Performance management is largely employed in both public and private sectors. The performance management models in the business organization are frameworks that support the operation of aligning the individual employee functionality with the organizational objectives, driving overall success, and fostering continuous enhancement. These frameworks concentrate on generating a culture of performance, where the employees are engaged and motivated, contributing efficiently to the objective of an organization. Mostly, the traditional models rely on manual evaluations, which result in subjective predictions and also require more labour. Therefore, automated performance management models are being developed these days. Deep learning approaches can highly improve performance management in business organizations, and offer actionable insights. These models can automate operations, minimize manual errors, and enhance operational efficiency by validating the huge data sources. Although the deep learning-aided models are effective in performance management, very limited works have been performed in the past few days based on deep learning. Also, the designed models fail to offer more predicted accuracy due to these models' complex architectures and limited feature extraction capacities. Therefore, this work presents an advanced performance management approach in business organizations. Fig.3 provides the overall view of the designed performance management framework in business organizations.

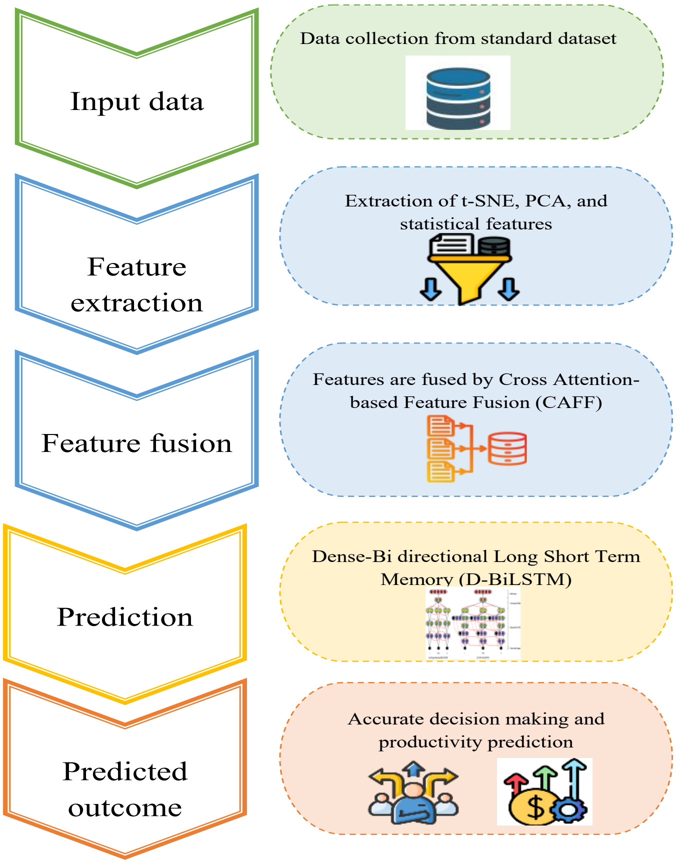


Fig. 3. Overall view of the designed performance management framework in a business organization

<u>Justification for the use of a recurrent-based model:</u> The input dataset contains sequential and time-dependent patterns. Recurrent architectures like RNN and LSTM models are capable of capturing temporal dependencies and sequential relationships in data. By using a recurrent model, feature interactions are precisely modeled and it leads to more accurate predictions and reliable decision-making outcomes. Therefore, D-BiLSTM is presented in this work for predicting the business performance to enhance their growth. D-BiLSTM processes the fused features in both forward and backward directions without high computational complexity issues.

This work presents an advanced deep-learning model for performance management in business organizations. This approach helps to predict the productivity of the organization to enhance the overall performance of the organization. At first, this work aggregates significant data for validation from online resources. Further, for improving the model performance, the designed work extracts the features from the original data. Here, the t-SNE, PCA, and statistical features are extracted and provided for the subsequent fusion operation. In this, the CAFF technique is supported, which effectively fuses all the feature sets and minimizes the redundant data for improving the prediction process. The fused feature is then subjected to the D-BiLSTM technique as input for decision-making and also for predicting the productivity of the organization. Finally, the predicted outcome is achieved, and the designed model's performance is examined with other related approaches to ensure the model's supremacy. Temporal window size and sequence construction details of the proposed model are given in Table 2.

Table 2: Temporal window size and sequence construction details of proposed model

Component	Description
Temporal Window Size	10 time steps
Sequence Construction	Sliding window approach
Input Features per Step	64 features
Input Shape	(10, 64)
Target Alignment	Label assigned to the final time step of each sequence
Window Stride	1 (overlapping sequences)
Padding Strategy	No padding (only valid windows used)
Total Dataset Size	1197 records
Effective Sequence Samples	~1188 sequences (1197 − 9)

V. Results and Discussion

Experimental Setup

Python was considered for validating the designed performance management framework in business organizations. Here, the performance validations were done for this framework by leveraging the traditional models including 'Support Vector Machine (SVM) [XX], Deep Neural Network (DNN) [VII], Recurrent Neural Network (RNN) [II], and LSTM [IV]'.Implementation details are given in Table 3.

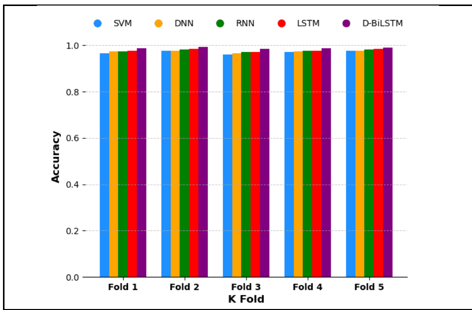
Table 3: Implementation details

Total Trainable Parameters	~95K – 110K
Dropout Rates	0.3 / 0.3 / 0.2
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	100
Validation	5-fold cross-validation

Performance Analysis

The designed D-BiLSTM-aided performance management framework is analyzed in Fig.4 over traditional models. This experiment considered the k-fold values (1 to 5) for evaluating the model functionality. Moreover, it considers various performance measures for showcasing the designed approach's ability in the performance management operation. At the 3rd k-fold value, the Mean Absolute Error (MAE) of the suggested D-BiLSTM is reduced by 13.33% of SVM, 10.8% of DNN, 7.5% of

RNN, and 6.6% of LSTM, respectively. This experiment ensures that the designed D-BiLSTM ultimately enhances the performance and productivity of the business organization than the previous approaches. In addition, this designed system effectively supports faster decision-making and enhanced employee engagement.



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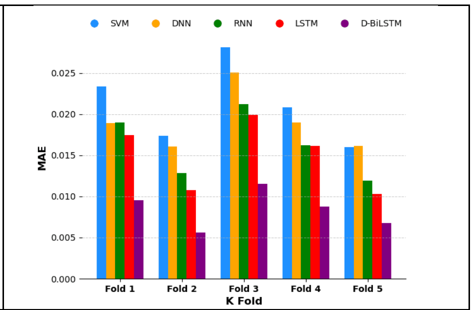

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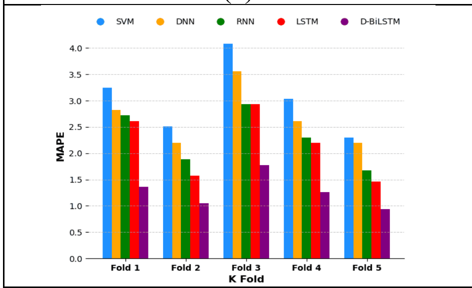

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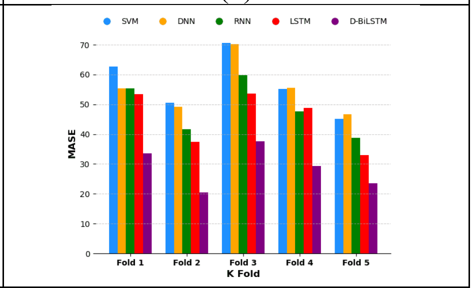

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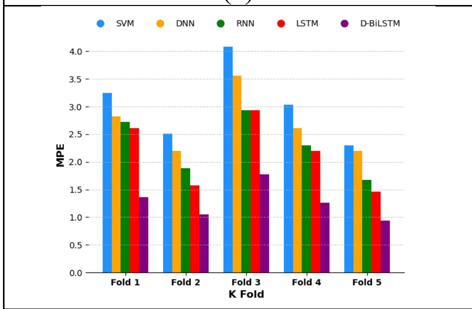

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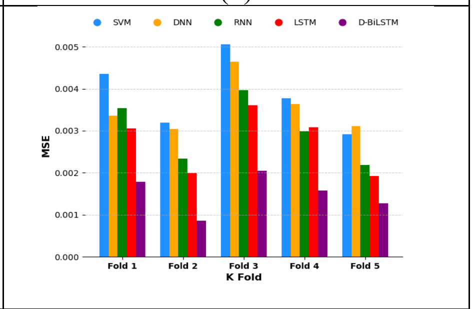

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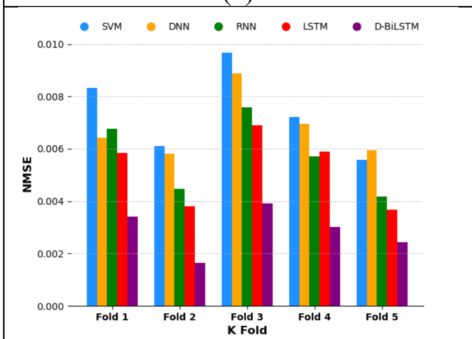

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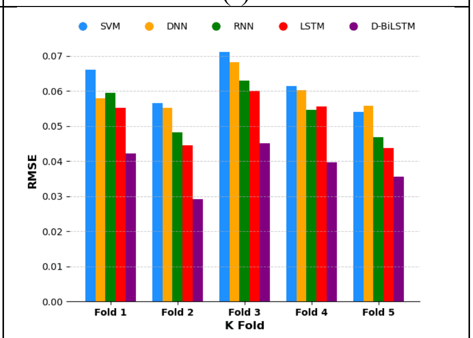

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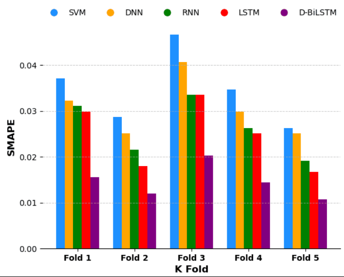


(i)

Fig. 4. Performance investigation of designed D-BiLSTM-aided performance management in business organization over conventional models in terms of (a) Accuracy, (b) MAE, (c) Mean Absolute Percentage Error (MAPE), (d) Mean Absolute Scaled Error (MASE), (e) Mean Percentage Error (MPE), (f) Mean Squared Error (MSE), (g) Normalized Mean Squared Error (NMSE), (h) Root Mean Squared Error (RMSE), and (i) Symmetric Mean Absolute Percentage Error (SMAPE)

Comparative Analysis

The comparative analysis of the proposed D-BiLSTM model against existing approaches like gradient boosting regression is provided in Table 4. Table 5 presents the average accuracy and MAE across 5-fold cross-validation. The accuracy of the proposed D-BiLSTM model in predicting the business performance is 91.43%, while techniques like random forest, XGboost, RNN and LSTM obtained an accuracy of 83.07%, 85.82%, 86.88% and 88.72% for the Fold-5 analysis. Handling the temporal dependencies and sequential patterns in business performance data is not efficiently managed by the random forest and XGBoost models. D-BiLSTM addresses this limitation by processing sequences in both forward and backward directions. Moreover, the proposed D-BiLSTM capture complex temporal context when compared to other models.

Table 4: Comparative Analysis of the Proposed Approach among 5fold Variation

Accuracy					
Techniques	**Fold 1**	**Fold 2**	**Fold 3**	**Fold 4**	**Fold 5**
Random forest [XXIV]	82.58	83.11	82.94	83.36	83.07
XGboost [XXIV]	85.12	85.46	85.73	86.01	85.82
RNN [II]	86.48	86.72	86.95	87.14	86.88
LSTM [IV]	88.21	88.44	88.66	90.02	88.72
Proposed D-BiLSTM	90.84	91.02	91.16	88.83	91.43

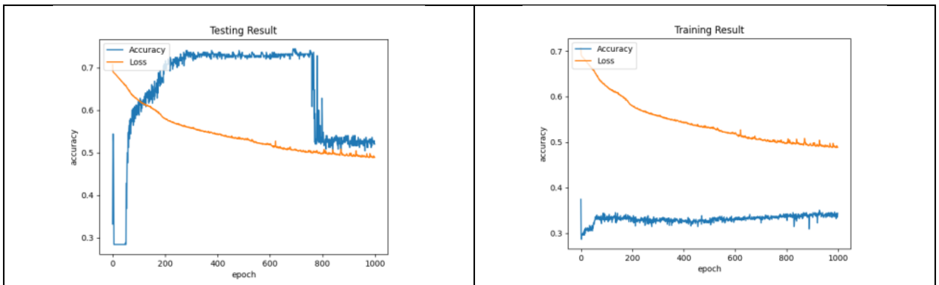
Table 5: Cross-fold performance evaluation

Techniques	Accuracy (%) (Mean ± SD)	MAE (Mean ± SD)
Random forest [XXIV]	88.10 ± 0.18	0.313 ± 0.005
XGboost [XXIV]	88.75 ± 0.20	0.304 ± 0.004
RNN [II]	89.30 ± 0.20	0.293 ± 0.004
LSTM [IV]	89.83 ± 0.16	0.290 ± 0.003

Proposed D-BiLSTM	91.16 ± 0.23	0.271 ± 0.005
Performance evaluation across multiple random seeds		
Proposed D-BiLSTM	91.10 ± 0.12	0.272 ± 0.004
XGBoost	88.75 ± 0.10	0.304 ± 0.003
Random Forest	88.12 ± 0.14	0.313 ± 0.005

Training and Testing Analysis

The testing and training accuracy and loss over 1,000 epochs are showcased in Fig. 5. The accuracy of the proposed model improves and stabilizes while the loss decreases during training. This evaluation helps to analyze the effectiveness of the suggested model after training. As per the analysis, the generalization ability of the implemented model is better.



(a) (b)

Fig. 5: Model performance evaluation with respect to a) Training and b) Testing

Paired t-test Analysis

A paired t-test was conducted on the 5-fold accuracies to evaluate the efficiency of the proposed model, and the results are shown in Table 6. As per the results, the observed improvements of the proposed D-BiLSTM over baseline models were statistically significant. Therefore, the reliability of the presented D-BiLSTM approach for business performance prediction is high.

Table 6 : Paired t-test outcomes

Technique comparison	Mean Difference	Approx. p-value	Significant
D-BiLSTM vs RF	3.06	<0.001	Yes
D-BiLSTM vs XGboost	2.31	<0.005	Yes
D-BiLSTM vs RNN	1.55	<0.01	Yes
D-BiLSTM vs LSTM	1.33	<0.01	Yes

V. Conclusion

A new automated technique for performance management of business organizations was developed in this work. At first, the available data was aggregated from an online resource. From the input data, the features such as t-SNE, PCA, and statistical features were extracted. These features were fused by the CAFF approach to minimze the redundancy. Subsequently, the fused feature was subjected to the D-BiLSTM for predicting productivity and also for decision-making. Finally, the performance of the model was examined over existing models. At the 5th k-fold value, the accuracy of the suggested D-BiLSTM was enhanced by 3.06% of SVM, 2.55% of DNN, 2.04% of RNN, and 1.42% of LSTM, respectively. From the outcomes, it has been confirmed that the implemented performance management approach was more effective and accurate than the previous approaches. By accurately predicting and making decisions, the designed framework helps the organizations to achieve the overall goal. Though this designed framework is effective and robust in performance management, this model was only analyzed with a single dataset, which may limit its generalization ability. Therefore, in future work, the designed framework will be analyzed with large and complex data sources to ensure its generalization abilities.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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