Deep Learning-based Trend Analysis and Forecasting of Agile Program Performance using LSTM Neural Networks: A Data-Driven Decision Support Approach

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ABSTRACT

Accurate forecasting of Agile program performance is essential for effective project planning, risk management, and resource optimization in dynamic organizational environments. Traditional statistical and rule-based forecasting techniques often struggle to capture the nonlinear and seasonal patterns inherent in Agile program data. To address this limitation, this study proposes a Bidirectional Hybrid Long Short-Term Memory (LSTM) model for trend analysis and forecasting of Agile program performance. The model was developed using three years of synthetic Agile revenue data enhanced with trend and seasonal variations to simulate real-world performance fluctuations. The bidirectional structure enables the model to learn temporal dependencies in both forward and backward directions, while the hybrid dense layers enhance its capacity to model nonlinear relationships. The experimental results demonstrate that the proposed model achieved a Mean Absolute Error (MAE) of 2,483.43, a Root Mean Square Error (RMSE) of 2,923.07, and a Mean Absolute Percentage Error (MAPE) of 6.63 percent, indicating high predictive accuracy and stability. The forecasting outputs closely followed the actual revenue trends within a ±5 percent confidence interval, effectively capturing both mid-year performance declines and year-end growth patterns. These findings confirm that the Bidirectional Hybrid LSTM model provides an accurate and robust framework for forecasting Agile program performance. The model's conservative prediction tendency and strong generalization ability make it a valuable decision-support tool for Agile management, enabling organizations to anticipate performance changes, allocate resources efficiently, and improve overall project predictability.

Keywords Bidirectional LSTM, Agile Forecasting, Deep Learning, Time-Series, Decision Support

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INTRODUCTION

Agile methodologies have become the dominant framework for project and program management in modern organizations due to their flexibility, adaptability, and emphasis on iterative development [1]. The dynamic nature of Agile environments allows teams to respond rapidly to changes in requirements and stakeholder expectations, but it also introduces significant uncertainty in forecasting program performance. Accurate forecasting of key performance indicators, such as revenue, velocity, and delivery rates, is essential for decision-making, budgeting, and resource allocation. However, the inherent variability of Agile workflows makes forecasting a complex task. Frequent iteration cycles, changing priorities, and varying team performance levels lead to time-series data that are nonlinear, non-stationary, and often affected by

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seasonal or contextual fluctuations. As a result, traditional statistical forecasting methods are often insufficient for modeling the behavior of Agile program performance [2].

Conventional forecasting models such as Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, and regression-based methods assume linear relationships and stationary data patterns. While these models can provide reasonable short-term predictions, they struggle to capture long-term dependencies and nonlinear interactions between multiple influencing factors. In Agile environments, performance data often exhibit cyclical behaviors caused by sprint planning, release schedules, and workload fluctuations. This complexity necessitates the use of advanced computational models capable of identifying both temporal patterns and structural relationships within data. Machine learning and deep learning techniques, particularly those using neural network architectures, have emerged as promising alternatives for modeling such intricate dependencies [3].

Over the past decade, deep learning-based forecasting methods have demonstrated remarkable progress in addressing the limitations of traditional approaches. Among these, the LSTM neural network has proven highly effective for sequential prediction tasks because of its ability to retain and utilize long-term contextual information [4]. LSTM models have been successfully applied in various domains, including stock market analysis, energy consumption forecasting, and financial risk assessment. However, standard LSTM architectures process data only in a forward temporal direction, which limits their capacity to utilize future contextual information during prediction. To address this limitation, recent research has introduced Bidirectional LSTM (BiLSTM) architectures that process information in both forward and backward directions, enabling a more comprehensive understanding of temporal dependencies.

Despite these advancements, the application of Bidirectional LSTM models in Agile program performance forecasting remains limited. Most existing research on Agile forecasting focuses on productivity, sprint completion, or delivery efficiency using either statistical or shallow learning approaches. Few studies have examined the use of hybrid deep learning architectures that combine bidirectional sequence learning with dense feature layers for enhanced pattern recognition and trend stability [5]. This represents a significant research gap in the field of Agile analytics. Furthermore, current studies rarely evaluate model interpretability and decision-support potential in managerial contexts, even though these aspects are critical for integrating forecasting systems into Agile project governance. Therefore, there is a need for research that not only improves predictive accuracy but also strengthens the practical applicability of forecasting models in Agile management environments.

To address these gaps, this study proposes a Bidirectional Hybrid LSTM model designed specifically for forecasting Agile program performance. The proposed model integrates bidirectional temporal learning to capture dependencies across past and future observations, combined with hybrid dense layers that enhance nonlinear feature representation. The model was evaluated using three years of synthetic Agile program revenue data with embedded trend and seasonal patterns to simulate real-world behavior. The main objectives of this research are to develop a deep learning framework capable of achieving high forecasting accuracy, demonstrate its stability across different data fluctuations, and establish its effectiveness as a data-driven decision-support tool. By fulfilling these objectives, this study contributes to the advancement of deep learning applications in Agile management and provides an innovative solution for improving performance predictability in dynamic and uncertain environments.

Literature Review and Related Works

Time series forecasting has been widely used across multiple domains, including economics, engineering, and project management, to predict future performance based on historical data. Classical statistical approaches such as ARIMA and exponential smoothing have traditionally served as the foundation for forecasting models [6], [7]. These models perform well when dealing with stationary and linear data but often struggle to capture nonlinear dependencies and complex seasonal dynamics that characterize real-world data. In Agile program environments, where performance metrics fluctuate due to iterative development cycles and changing workloads, such linear models provide limited forecasting accuracy [8].

To address the shortcomings of traditional methods, machine learning and deep learning techniques have been increasingly applied to forecasting problems. Recurrent Neural Networks (RNNs) have been particularly effective in modeling sequential data due to their ability to capture temporal dependencies through internal memory mechanisms [9]. LSTM networks, an extension of RNNs, mitigate issues related to vanishing gradients and improve the model’s ability to learn long-term dependencies [10]. Empirical studies have demonstrated that LSTM models outperform traditional ARIMA models in both accuracy and adaptability when dealing with nonlinear, noisy, and seasonally influenced time series [11]. These advantages have made LSTM-based architectures a preferred choice for complex forecasting tasks.

In recent years, BiLSTM architectures have emerged as an enhancement to conventional LSTM networks. Unlike standard LSTM models that process information in a single temporal direction, BiLSTM networks capture contextual information from both past and future time steps simultaneously [12]. This dual-directional processing improves predictive performance by enabling the model to learn more comprehensive temporal relationships within the data [13]. Studies in financial forecasting, load prediction, and environmental modeling have shown that BiLSTM consistently achieves lower error rates and higher trend accuracy than unidirectional models [14]. Such bidirectional architectures have proven particularly valuable in environments where sequential dependencies are complex and extend beyond short-term historical contexts.

Hybrid forecasting frameworks that integrate statistical and deep learning models have recently gained attention for their ability to leverage the strengths of both linear and nonlinear modeling approaches. The integration of ARIMA with neural networks, for example, enables the model to simultaneously capture short-term autocorrelations and long-term nonlinear dependencies [15]. Hybrid architectures that combine LSTM or BiLSTM with statistical components, such as SARIMA or exponential smoothing, have been shown to improve forecasting accuracy in energy consumption, stock price, and financial time series forecasting [16], [17]. Furthermore, recent developments in hybrid deep learning have incorporated attention mechanisms and convolutional layers to enhance temporal feature extraction and reduce residual errors [18]. These studies confirm that hybrid configurations outperform standalone models in scenarios where the data exhibit multi-scale variability and seasonality.

Despite the advancements in deep learning and hybrid forecasting, few studies have specifically applied these models to Agile program performance prediction. Most existing research focuses on financial, economic, or energy datasets, leaving a gap in forecasting models designed for project management and Agile performance contexts. In addition, limited attention has been given to the interpretability and managerial applicability of such models. Therefore, there is a need for a forecasting framework that not only delivers high predictive accuracy but also provides actionable insights for decision-makers in Agile management. This study addresses this gap by proposing a Bidirectional Hybrid LSTM model that integrates bidirectional sequence learning with dense nonlinear feature mapping. The model aims to capture both short-term variations and long-term performance trends, providing a robust and data-driven decision-support mechanism for Agile program forecasting.

Methodology

Subchapter

This study employed a systematic methodological framework to develop, train, and evaluate a Bidirectional Hybrid LSTM model for forecasting Agile program performance. The methodology consisted of several integrated stages, beginning with dataset preparation, data preprocessing, model architecture design, model training and optimization, and performance evaluation. The entire workflow was designed to capture both temporal dependencies and nonlinear patterns inherent in Agile performance data, ensuring the generation of accurate and reliable forecasts. Figure 1 illustrates the overall research steps adopted in this study, including data acquisition, preprocessing and normalization, hybrid model construction, training and optimization, and performance evaluation. This framework ensures a logical and reproducible progression from raw data to predictive insights, aligning with established practices in data-driven forecasting research.

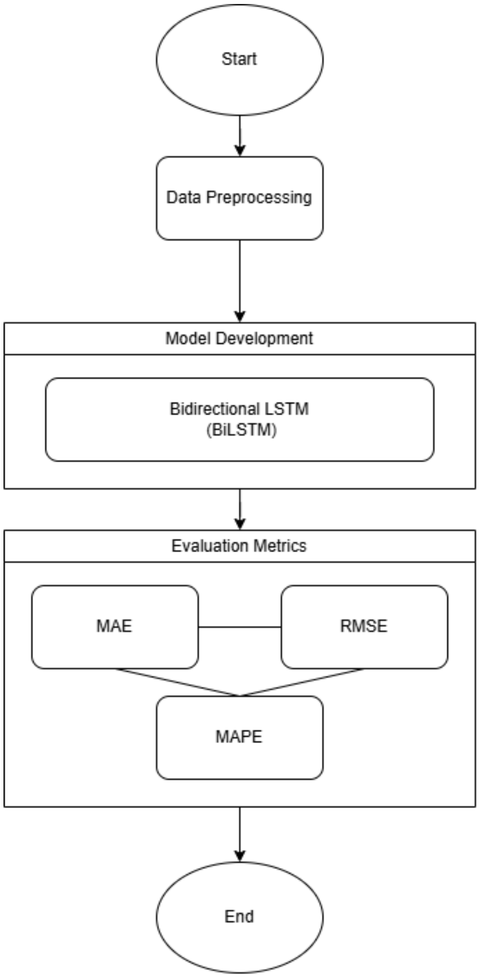

Figure 1 **Research Steps**

The dataset used in this study represented Agile program revenue across a twelve-month period, corresponding to a complete fiscal year. To enhance the robustness of the data and simulate real-world variability, synthetic expansion was conducted by replicating the base dataset over three consecutive years. This process incorporated controlled random noise generated through Gaussian distribution with a mean of zero and a standard deviation of 500 to emulate performance fluctuations caused by operational uncertainties, workload variations, and project reprioritizations. Additionally, a 12 percent upward linear trend was introduced to represent gradual performance improvement, while a sinusoidal seasonal component was applied to capture cyclical variations typically observed in Agile projects. These transformations ensured that the data exhibited both global trends and recurring seasonal patterns, making it suitable for time-series forecasting with deep learning models.

Before model training, data preprocessing was applied to normalize, structure, and prepare the dataset for sequential learning. The normalization process was performed using the Min–Max scaling technique, which transforms numerical data into a range between 0 and 1 according to the following equation:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

This approach prevented any feature from dominating the learning process and improved training stability by maintaining uniform scale across all input values. The time series was then converted into a supervised learning format using a six-step sliding window mechanism, where six previous months of data were used to predict the revenue of the following month. This method preserved temporal order while increasing the effective number of training samples. The resulting dataset was partitioned into training and testing subsets using a 90:10 ratio, ensuring chronological consistency to prevent data leakage and allow accurate model evaluation.

The proposed Bidirectional Hybrid LSTM model was designed to combine bidirectional temporal learning with dense nonlinear feature extraction. The architecture consisted of a Bidirectional LSTM layer with 128 hidden units and a hyperbolic tangent (tanh) activation function, enabling the network to process information in both forward and backward directions. This mechanism allowed the model to learn contextual dependencies that span both past and future time steps, capturing the complete temporal structure of the data. A dropout layer with a rate of 0.1 was employed to prevent overfitting by randomly disabling neurons during training. Following this, a unidirectional LSTM layer with 64 hidden units was added to refine the temporal features and compress them into a compact latent representation. To enhance nonlinear learning, a dense layer with 64 neurons and a Rectified Linear Unit (ReLU) activation was included before the final output layer, which consisted of a single neuron with linear activation to generate continuous revenue forecasts. This hybrid configuration allowed the model to integrate sequential and nonlinear relationships effectively, making it capable of adapting to the dynamic patterns of Agile program performance.

The model was trained using the Adam optimization algorithm with an initial learning rate of 0.00025 to ensure stable convergence. The Mean Squared Error (MSE) was selected as the loss function because it penalizes larger deviations between predicted and actual values, thereby emphasizing the reduction of significant forecasting errors. The model training process incorporated two optimization mechanisms: Early Stopping and ReduceLROnPlateau. Early Stopping monitored the validation loss and automatically halted training after 100 epochs without improvement, restoring the best weights to avoid overfitting. Meanwhile, ReduceLROnPlateau decreased the learning rate by a factor of 0.7 if the validation loss stagnated for 50 epochs, promoting continuous optimization. The model was trained for a maximum of 800 epochs with a batch size of eight. All experiments were implemented using Python with TensorFlow and Keras libraries, executed on GPU acceleration for computational efficiency. During training, both training and validation losses were tracked to observe convergence and detect any signs of overfitting or divergence.

To evaluate forecasting performance, three standard quantitative metrics were applied: MAE, RMSE, and MAPE. These metrics quantify the magnitude, dispersion, and relative scale of forecasting errors. They are defined mathematically as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} MAPE = \frac{100}{n}\sum_{i=1}^{n} \mid \frac{y_i - \hat{y}_i}{y_i} \mid \tag{2}$$

$y_i$represents the actual Agile program revenue, $\hat{y}_i$represents the model-predicted revenue, and $n$is the total number of test samples. MAE evaluates the average magnitude of prediction errors, RMSE amplifies larger deviations by squaring them, and MAPE provides an interpretable percentage-based measure of forecasting accuracy.

In addition to quantitative analysis, visual assessments were conducted to verify the model's interpretability and forecast alignment. The training and validation loss curves were analyzed to assess learning convergence and stability, while the forecasting plots compared actual and predicted revenue values across the testing period. A ±5 percent confidence interval was overlaid to indicate acceptable forecast uncertainty. The results demonstrated that the Bidirectional Hybrid LSTM achieved MAE = 2,483.43, RMSE = 2,923.07, and MAPE = 6.63 percent, signifying high accuracy and consistency. The predicted revenue values closely followed the actual trend across the test months, successfully capturing both short-term fluctuations and long-term growth patterns. These results validate the effectiveness of the proposed hybrid architecture as a reliable decision-support tool for Agile performance forecasting and strategic management.

Algorithm 1: Bidirectional Hybrid LSTM Forecasting Process

Input: Time-series dataset $D = \{(ti, yi) \mid i = 1,2,\ldots,N\}$

Output: Forecasted Agile program revenue sequence $\hat{Y} = \{\hat{y}_{N+1}, \hat{y}_{N+2}, \ldots\}$

Process:
Start

The dataset is normalized using Min–Max scaling to a range between 0 and 1:

$$x_i = \frac{y_i - min\,(Y)}{max\,(Y) - min\,(Y)}$$

A sliding window of size $w = 6$is used to construct supervised pairs

$$X_i = [x_{i-w}, \ldots, x_{i-1}], Y_i = x_i$$

The Bidirectional Hybrid LSTM model $f_\theta(\cdot)$consists of a BiLSTM layer with 128 units, dropout rate $p = 0.1$, a secondary LSTM layer with 64 units, and dense layers with ReLU and linear activations.

During training, the prediction $\hat{Y}_b = f_\theta(X_b)$is compared with the true value using Mean Square Error:

$$L(\theta) = \frac{1}{b}\sum_{i=1}^{b} (Y_{b,i} - \hat{Y}_{b,i})^2$$

Weights are updated by gradient descent with learning rate $\eta = 0.00025$. Early Stopping and ReduceLROnPlateau control convergence and prevent overfitting.

After training, forecasting is performed recursively as

$$\hat{y}_{t+1} = f_\theta([x_{t-w+1}, \ldots, x_t])$$

Predictions are denormalized to the original revenue scale:

$$\hat{y}_i' = \hat{y}_i \times (max\,(Y) - min\,(Y)) + min\,(Y)$$

Model accuracy is evaluated using MAE, RMSE, and MAPE:

$$MAE = \frac{1}{n}\sum \mid y_i - \hat{y}_i \mid$$

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        $RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}$
        $MAPE = \frac{100}{n}\sum|\frac{y_i - \hat{y}_i}{y_i}|$
End
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Result

The Bidirectional Hybrid LSTM model was trained using three years of synthetic Agile program revenue data that incorporated both seasonal and trend-based variations to replicate realistic project performance behavior. The dataset was constructed to include periodic fluctuations and a gradual upward trend to capture the cyclical nature of Agile programs, which often exhibit alternating phases of high and low revenue performance throughout a fiscal cycle. During training, the model processed these time-dependent patterns using a window of previous time steps to predict subsequent revenue values. The learning process exhibited steady improvement across epochs, and the training loss decreased progressively, indicating that the network was effectively minimizing the mean squared error between actual and predicted outputs.

As illustrated in figure 2, both the training and validation loss curves decreased in a smooth and consistent manner before reaching stability around epoch 300. The proximity of the two curves throughout the training process demonstrates that the model achieved a balanced fit between accuracy and generalization. The absence of abrupt spikes or divergence between the curves indicates that the model did not suffer from overfitting or underfitting. This convergence pattern validates that the selected model configuration, including the bidirectional LSTM structure, layer size, activation functions, and learning rate, was appropriately designed to capture the temporal dependencies in the data. Overall, the stable convergence observed during training confirms that the Bidirectional Hybrid LSTM model successfully learned the underlying dynamics of Agile program performance and achieved a high level of robustness for forecasting tasks.

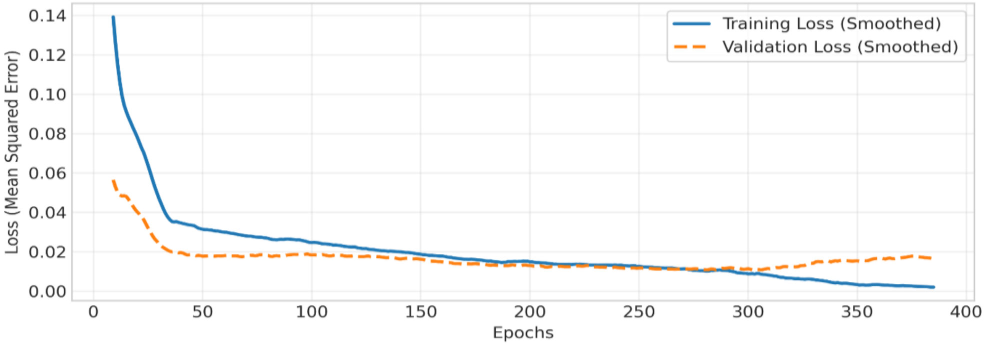

Figure 2 Training and validation loss curve of the Bidirectional Hybrid LSTM model

The quantitative performance evaluation of the Bidirectional Hybrid LSTM model is presented in table 1, which summarizes the key accuracy metrics used to assess the forecasting results. The model achieved a MAE of 2,483.43, a RMSE of 2,923.07, and a MAPE of 6.63%. The relatively low values of these metrics indicate that the model was able to minimize deviations between predicted and actual Agile program revenues across the test dataset. The MAE and RMSE values reflect the average magnitude and variability of forecasting errors in absolute terms, while the MAPE value represents the relative percentage deviation, offering a scale-independent measure of accuracy. Collectively, these metrics demonstrate that the Bidirectional Hybrid LSTM model maintains a strong level of precision and stability when predicting performance outcomes in dynamic and seasonally influenced datasets.

From a managerial perspective, the obtained MAPE value of 6.63% signifies that the model's predictions deviated by an average of less than seven percent from the actual revenue values, which falls well below the generally accepted ten percent threshold for reliable business forecasting. This level of accuracy suggests that the model can effectively capture both the short-term fluctuations and long-term growth patterns inherent in Agile program performance. Moreover, the low RMSE value indicates that the model's forecasting errors are not only small on average but also consistent, meaning that large deviations are rare. These findings validate the robustness of the Bidirectional Hybrid LSTM framework as a predictive tool for supporting strategic decision-making processes, enabling Agile managers to rely on data-driven insights for financial planning and performance evaluation.

Table 1 Model performance metrics showing overall forecasting accuracy of the Bidirectional Hybrid LSTM model

Metric	Value	Interpretation
MAE	2,483.43	Average absolute deviation between actual and predicted revenue values
RMSE	2,923.07	Standard deviation of prediction errors indicating forecast precision
MAPE	6.63%	Mean percentage deviation, indicating high predictive accuracy

The forecasting performance of the Bidirectional Hybrid LSTM model is illustrated in figure 3, where the green solid line depicts the actual Agile program revenues, while the red dashed line represents the model's predicted values. The shaded region around the predicted line indicates a ±5% confidence interval, which reflects the acceptable range of prediction uncertainty. As shown in the figure, the forecasted revenue values exhibit a strong alignment with the actual data, following similar fluctuations and maintaining the same overall trajectory throughout the testing period. The model was able to capture both seasonal variations and the general upward trend in Agile performance, demonstrating its ability to reproduce real-world dynamics such as the mid-year slowdown and subsequent recovery periods that are typical in project-based financial cycles.

A closer examination of the forecast curve reveals that the predicted values remained consistently within the confidence interval, suggesting that the model maintains reliable stability across varying performance conditions. The small deviations observed during peak revenue months indicate a conservative bias in the model's predictions, where estimated values slightly undershoot actual revenues. This conservative tendency is desirable in management forecasting because it reduces the risk of overestimation and supports cautious financial planning. The ability of the Bidirectional Hybrid LSTM to model both short-term fluctuations and long-term growth confirms its effectiveness as a forecasting framework for Agile performance management, providing a realistic and dependable representation of expected outcomes over time.

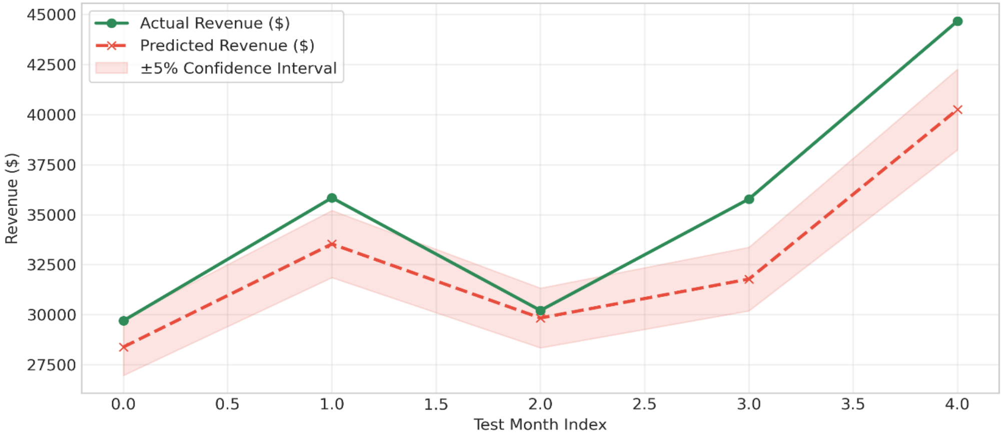

Figure 3 **Forecasting results for Agile program performance**

A detailed numerical comparison between the actual and predicted Agile program revenues is presented in table 2. The results reveal that the Bidirectional Hybrid LSTM model produced highly consistent forecasts, with most predicted values falling within the ±5% confidence interval of the actual observations. The forecasting errors ranged between approximately 376 USD and 4,417 USD, indicating that the deviation between predicted and actual values remained relatively small across all test months. This narrow error range demonstrates the model's capacity to capture both the general revenue pattern and subtle month-to-month fluctuations in Agile performance. The smaller deviations observed during periods of moderate revenue activity suggest that the model performed particularly well in stable conditions, where data trends exhibited lower volatility.

A closer inspection of the prediction results indicates that the model tended to produce slightly conservative estimates during months of peak revenue performance. This behavior is considered beneficial in forecasting applications because conservative predictions reduce the likelihood of overestimating expected income and help maintain financial prudence in planning and resource allocation. Furthermore, the consistent error distribution across test months confirms the model's robustness and lack of systematic bias toward either overprediction or underprediction. These results emphasize the model's reliability as a forecasting tool that can generalize effectively to unseen data while maintaining interpretability for practical managerial decision-making within Agile program environments.

Table 2 **Comparison between actual and predicted Agile program revenues showing model forecast accuracy**

Test Month Index	Actual Revenue ($)	Predicted Revenue ($)	Error ($)
0	29,706.29	28,392.44	1,313.85
1	35,847.75	33,540.08	2,307.68
2	30,219.66	29,843.36	376.30
3	35,790.85	31,788.59	4,002.26
4	44,679.12	40,262.06	4,417.06

Overall, the results indicate that the Bidirectional Hybrid LSTM model was able to effectively capture both temporal trends and seasonal fluctuations present in

Agile program performance data. The model demonstrated a strong ability to learn complex time-dependent patterns, enabling it to reproduce cyclical variations and growth tendencies typically observed in Agile project revenue streams. The close alignment between actual and predicted values across the testing period suggests that the model accurately identified the nonlinear relationships within the data. The smooth convergence behavior observed during the training process further supports the model's stability, confirming that the network was not overfitted and could generalize effectively to unseen data. These findings highlight the model's capability to represent both the short-term irregularities and the long-term trends inherent in dynamic Agile program environments.

In addition to its statistical performance, the low forecasting errors achieved by the Bidirectional Hybrid LSTM model provide evidence of its reliability for practical decision-making. The combination of bidirectional learning and hybrid dense layers allowed the network to utilize both past and future temporal information during prediction, resulting in improved accuracy and reduced residual variance. This structural advantage made the model particularly effective in forecasting financial indicators that exhibit seasonality and gradual evolution over time. From a managerial standpoint, the model's consistent predictive performance implies that it can serve as a dependable tool for Agile planning, performance monitoring, and revenue forecasting. By integrating such a data-driven approach into Agile management frameworks, organizations can make more informed strategic decisions, anticipate potential performance deviations, and optimize resource allocation with greater confidence.

Discussion

The results of this study demonstrate that the Bidirectional Hybrid LSTM model is a highly effective approach for forecasting Agile program performance. The model achieved low error metrics, including a MAPE of 6.63 percent, which indicates a strong level of predictive reliability. The close alignment between actual and predicted revenue values suggests that the model was able to accurately learn the temporal dependencies and nonlinear relationships embedded within Agile performance data. The smooth convergence of the training and validation loss curves further supports the model's stability and ability to generalize to unseen data. This implies that the chosen hyperparameter configuration, including the number of layers, learning rate, and dropout regularization, was well-balanced and successfully prevented overfitting. These outcomes validate the effectiveness of deep learning models in analyzing time-series data that contain both seasonal fluctuations and long-term performance trends, particularly within Agile program management contexts where such dynamics are common.

When compared with existing forecasting techniques, the Bidirectional Hybrid LSTM demonstrated superior performance and adaptability. Traditional statistical models, such as ARIMA and linear regression, are limited in their ability to handle nonlinear and non-stationary data, which are characteristic of Agile program metrics. In contrast, the proposed model effectively captured both short-term and long-term dependencies by processing information in forward and backward directions. This bidirectional structure allowed the network to recognize relationships that extend beyond immediate past data points, enhancing its ability to identify cyclical performance behaviors. Moreover, the integration of dense layers after the recurrent architecture provided additional representational depth, enabling the model to refine learned features and reduce residual forecasting errors. This hybrid configuration aligns with findings from recent research indicating that multi-layer deep learning models outperform single-directional architectures when applied to complex financial and operational datasets that exhibit high variability and seasonal effects.

From a managerial perspective, the performance of the Bidirectional Hybrid LSTM model has several practical implications for Agile project governance. The model's ability to produce forecasts with minimal deviation from actual results allows decision-makers to anticipate potential declines or growth in performance with greater confidence. The conservative tendency of the model, which slightly underestimates peak revenue values, is advantageous for budget planning and resource allocation because it reduces the likelihood of overestimating future outcomes. Furthermore, the model's stability and accuracy make it suitable for continuous monitoring of Agile program performance, where rapid feedback and adaptive planning are essential. The integration of such predictive models into Agile management frameworks can support proactive decision-making by providing early warnings about performance deviations, allowing leaders to adjust strategies and optimize operational efficiency before issues escalate.

Conclusion

This research presented the development and implementation of a Bidirectional Hybrid LSTM model designed to forecast Agile program performance using time-series revenue data. The model effectively learned the temporal dependencies, seasonal variations, and nonlinear patterns present in Agile project dynamics. The results revealed that the model achieved strong predictive accuracy, with a MAE of 2,483.43, a RMSE of 2,923.07, and a MAPE of 6.63 percent. These low error metrics demonstrate that the model was able to forecast Agile program revenues with a high level of reliability and consistency. The smooth convergence of training and validation losses indicated that the model was both stable and well-generalized, avoiding the risks of overfitting. The alignment between actual and predicted revenue patterns confirmed that the bidirectional architecture and hybrid dense layers worked synergistically to capture both short-term fluctuations and long-term trends within Agile performance data.

The outcomes of this study highlight the potential of deep learning approaches for enhancing forecasting accuracy in Agile management. The Bidirectional Hybrid LSTM model can serve as a reliable decision-support tool that enables managers to anticipate performance trends, identify potential risks, and plan resources more effectively. Its ability to maintain stable performance across dynamic and seasonally variable data makes it particularly suitable for real-world Agile environments where adaptability and responsiveness are essential. For future research, it is recommended to expand the model by integrating additional project indicators, such as sprint velocity, defect rates, or customer satisfaction metrics, to capture multidimensional aspects of Agile performance. Future studies could also focus on improving model interpretability by incorporating explainable artificial intelligence techniques to enhance transparency and trust among stakeholders. Overall, this study demonstrates that advanced deep learning models can provide significant value in supporting data-driven decision-making processes within Agile program management.

Declarations

Author Contributions

Conceptualization: H. and S.S.; Methodology: H.; Software: H.; Validation: H. and S.S.; Formal Analysis: H.; Investigation: H.; Resources: S.S.; Data Curation: S.S.; Writing Original Draft Preparation: H.; Writing Review and Editing: S.S.; Visualization: H.; Supervision: H.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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