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Sales Prediction Using LSTM and BiLSTM Models: A Deep Learning Approach for Time Series Forecasting

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Abstract

Accurate sales forecasting significantly impacts planning strategies, inventory control, and business operations. Traditional methods of forecasting are often inadequate in recognizing intricate, multidimensional trends over time in sales data. This paper focuses on evaluating the performance of Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) networks in forecasting sales time series. Due to their sophisticated nature, LSTM and BiLSTM networks are an appropriate choice for sales forecasting since they recognize sequential data patterns and long-range dependencies as well as bidirectional dependencies. This research entails the complete process of sales data from preprocessing and feature engineering to model training using LSTM and BiLSTM networks. Important evaluation metrics such as MAE, RMSE, and MAPE are used to compare the models' performances. Experimental results suggest that BiLSTM significantly outperforms LSTM in recognizing sales fluctuation patterns. This, in turn, generates more accurate forecasts. The results demonstrate the ability of deep learning techniques to improve the precision of sales forecasting and, in turn, assist companies in optimizing resource allocation and increasing profitability. Including factors such as economic indicators, industry benchmarks, and advertising would provide even more value in future model refinement.

Keywords: Time Series Forecasting, LSTM, BiLSTM, Sales Prediction, Deep Learning, Recurrent Neural Networks.

1 Introduction

It is crucial that accurate sales forecasting allows companies to make sound decisions on demand planning, inventory, resource planning, and finance planning. Intricate, non-linear trends in sales figures tend to be difficult for standard time series forecasting methods, such as Exponential Smoothing and Autoregressive Integrated Moving Average (ARIMA), to detect (Praveenraj et al., 2024). Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (BiLSTM) (Lasek et al., 2016), have been some of the most powerful techniques for improving time series prediction accuracy with the advent of deep learning (Lasek et al., 2016).

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LSTM networks are most appropriate for time series prediction tasks since they are capable of handling long-term dependencies in sequential data by mitigating the vanishing gradient issue (Sasikanth et al., 2025). BiLSTM, an improvement on LSTM, handles data in both directions to capture better past and future dependencies. As sales data is dynamic and is affected by customer behavior, economic patterns, and seasonality, deep learning algorithms such as LSTM and BiLSTM possess an enormous potential to enhance predictive accuracy (Zakaria & Zaki, 2025).

Moreover, the effectiveness of LSTM and BiLSTM in sales forecasting is primarily attributed to their ability to learn complex temporal patterns as well as how they adapt to changes within the datasets. Unlike traditional models, which rely on rigid, linear, and stationary assumptions, deep learning sales forecasting models respond to external factors such as promos, holidays, and market demand shifts (Odegua, 2019). These models utilize historical sales data to identify complex relationships and seasonality, ultimately leading to enhanced forecasting accuracy. In addition, advanced forecasting accuracy can be achieved from feature engineering, hyperparameter optimization, and the use of hybrid models. With LSTM and BiLSTM, organizations seeking data-backed insights to improve operational efficiency have powerful assets at their disposal.

The rest of this paper is structured as follows: Section II offers a literature review of deep learning models and time series forecasting. Section III discusses the method, from gathering data to preprocessing before model application. Experimental results and data are given and discussed in Section IV. Section V concludes the study and provides some potential directions for future research.

2 Related Works

Predictive analysis of sales is a technique that applies historical and existing sales information to predict future sales results and enhance business performance. Neural networks are the most suited technology for forecasting sales, as stated by Yasaman Ensafi et al (Nayak & Raghatate, 2024; Keller & Schwarz, 2022). Variability of the outcome can be minimized and accuracy enhanced with the application of data preprocessing, detrending, and deseasonalizing techniques. One of the primary scientific contributions of the paper is forecasting future sales using SARIMA, one of the leading traditional time-series forecasting techniques. Advanced forecasting techniques based on artificial neural networks, such as CNN, Prophet, and LSTM, are also utilized (Ensafi et al., 2022; Ma et al., 2016). Measurement precision techniques such as RMSE and MAPE are used to evaluate results (Ensafi et al., 2022).

Javad Feizabadi proposes NN and ARIMAX as ML-based forecasting techniques. As noted earlier, while the second method produced more accurate and "smoothed" predictions, the first method succeeded in capturing demand. This study has confirmed two research hypotheses: first, that a hybrid model is created using machine learning with leading indicators and time series models for demand forecasting; second, that the research illustrates the significant improvement in efficiency achieved with sophisticated forecasting techniques (Rakesh et al., 2024; Feizabadi, 2022).

As noted by Tonya Boone and others, they focus on the effects of the data explosion and its enlargement on item projection. This will spotlight time series data. This research also examines the relevance of this data for organisational forecasting and its potential use in understanding customer behaviour (Fildes et al., 2022). All classes of retailers have unique forecasting problems, in the opinion of Robert Fildes and others. Through precise sales forecasting, retailers can stock a specific number of items and make timely decisions. This article also evaluates the accuracy of the comparison study results (Lasek et al., 2016).

As asserted by A. Lasek et al., the use of demanding forecasting is vital for the effective yield or revenue management (RM) system in a restaurant (Harrison, 1965). The ability to make sales forecasts is essential for independent restaurants and for restaurant chains operating in the form of conglomerates (Harrison, 1965). Harrison reviews the range of published and employed short-term sales forecasting techniques (Liu et al., 2013). Moreover, two significant techniques aim to forecast seasonal sales. The first is Brown's non-seasonal one-parameter forecasting. These forecasts assist owners in making important decisions to optimize management, production, and inventory control (Davis & Mentzer, 2007). Discuss forecasting methods and the accuracy of reflecting market conditions. A multi-element process model for managing sales forecasting is proposed in this research (Cadavid et al., 2018). As stated, now forecasting professionals have the means to measure and observe how organizational attributes influence the sales prediction performance and organizational design (Dalrymple, 1987).

Processes like data mining, machine learning, artificial intelligence, and statistical modelling all play an integral role in predictive sales analysis, where they seek data patterns and trends to forecast future behaviour of targets or leads. (Jain et al., 2015; Ranjitha & Spandana, 2021). Also, predictive sales analysis aids in strategic and financial forecasting by pinpointing possible opportunities and estimating risks.

Dataset

This dataset aims to forecast the sales in multiple stores based on their locations. We obtained the data from Kaggle's website [https://www.kaggle.com/competitions/demand-forecasting/data]. At the Kaggle Store Item Demand Forecasting Challenge, the objective is to build and train a Deep learning model that can efficiently and accurately forecast the daily sales of various items in multiple stores for the next three months. Analysing historical sales data is a big part of estimating future demand. This is crucial for adequate inventory and supply chain management. Table 1 exemplifies the attributes of the dataset, showing the data snapshot.

- Date: The sales data record is timestamped, excluding the impact of holidays or store closures.
- Store: Each store is assigned a unique identification number.
- Item: Each item is assigned a unique identification number.
- Sales: The number of a particular item sold on that date in the specified store.

Table 1: Sample Dataset

	Date	Store	Item	Sales
0	2013-01-01	1	1	13
1	2013-01-02	1	1	11
2	2013-01-03	1	1	14
3	2013-01-04	1	1	13
4	2013-01-05	1	1	10

3 Methodology

Applying the pre-processing techniques for data cleaning and feature extraction processes using the dataset collected from the Kaggle website. Deep Learning Models like BiLSTM and LSTM are fitted to the dataset, and the accuracy measures MSE, MAE, and RMSE are calculated. The proposed architecture is shown in Figure 1, and this work concludes by finding the best model.

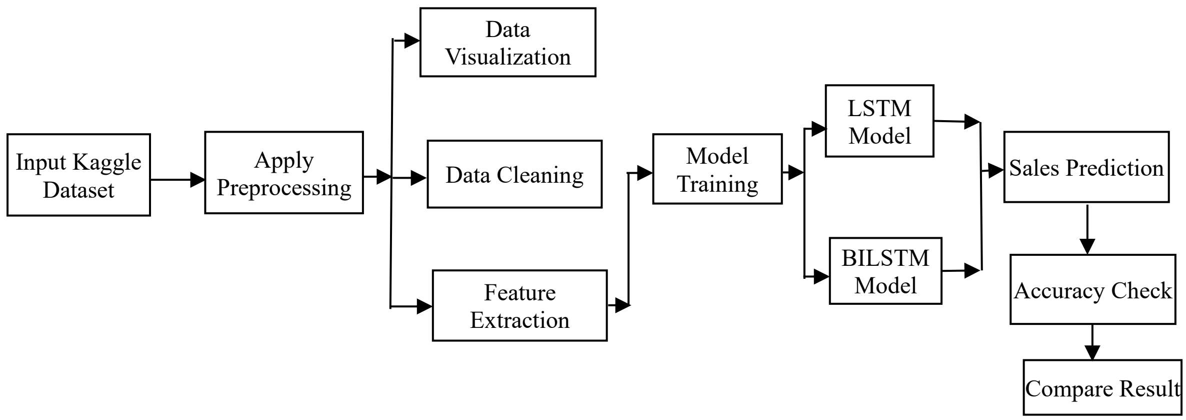

Figure 1: Proposed Architecture

Pre-processing

To get started with Kaggle's time series data for LSTM and BiLSTM models, we first check for a date, store, item, and sales columns before proceeding to load the data set. We now have a data set, which we continue to sort by store, item, and date to ensure the sequential relationship of the sales data set. For any missing data, we use the forward-fill and backward-fill techniques (Liu et al., 2013). Moreover, we derive features such as day, month, and year to add temporal patterns, which can be leveraged to make future sales predictions.

We apply MinMaxScaler to the sales data to ensure all values are within a specified range, which in turn helps stabilize the training process. Further, we convert the data into time series forecasting-friendly sequences, where a fixed window of past sales data, say 10-time steps, will be used as input in making the next value prediction. We apply all the steps for every store-item pair to ensure the individual sales patterns are retained.

Once the sequences have been created, we partition the dataset into training and testing subsets, usually in an 80-20 split. We also maintain the sequential order of data to avoid data leakage. The final dataset consists of X_train, X_test, y_train, and y_test, which can now be used to train LSTM and BiLSTM models (Wang & Yun, 2020). Also, the scaler that was fitted is retained to enable reverse transformation of the projections to the actual sales figures after the sales have been forecasted.

This approach to preprocessing the data ensures the time series data is clean, structured, scaled, and deep learning-ready because the models require well-structured data. With these preprocessing steps completed, the LSTM and BiLSTM models can accurately learn and forecast sales, which is crucial in demand planning for retail companies.

LSTM

The long short-term memory (LSTM) architecture of recurrent neural networks (RNNs) is used for sequential data and long-range dependencies. Unlike traditional RNNs, LSTMs incorporate a gating mechanism that allows the model to either remember or forget the input over time, helping to solve the vanishing gradient problem (Jain et al., 2015). Consequently, LSTMs are very useful for time series forecasting, such as projecting monthly sales trends. Figure 2 shows the cell Architecture diagram of the LSTM Model.

LSTMs consist of memory cells, which are the cell's components, and are responsible for the passage of knowledge through three essential gates.

The Forget Gate decides which information is no longer helpful and should be discarded from the cell state.

The Input Gate Decides which data gets added to the cell state as new information (Jain et al., 2015).

The Output Gate Controls the information that can be sent to the next hidden state (Jain et al., 2015).

LSTM networks can learn and model long-term dependencies of sequential data by efficiently controlling the information and gates of each memory cell.

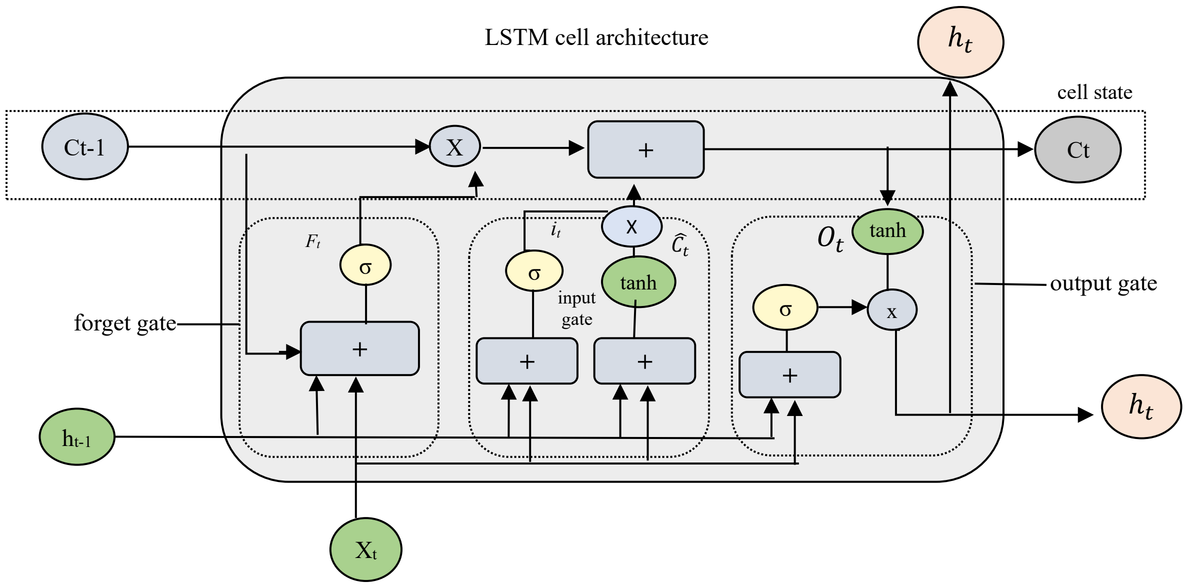

Figure 2: LSTM Architecture

Sales Forecasting Architecture [LSTM]

The LSTM model utilized in this investigation has several components that aim to obtain temporal patterns from the monthly sales data.

The LSTM model employs the following architecture:

A 12-month sales figures time series is the input to the model through the input layer.

LSTM Layer 1 comprises 100 LSTM units with ReLU activation, utilizing time-dependent features.

Dropout Layer 1: 20% of neurons are dropped to avoid overfitting the model.

LSTM Layer 2 contains 50 LSTM units, which are used to extract features in greater detail.

Dropout Layer 2: Another Dropout Layer is added to improve generalisation further.

Dense Output Layer: A fully connected layer with one neuron that predicts sales for the following month.

BiLSTM

Bidirectional Long Short-Term Memory (BiLSTM) is a complex neural network architecture that integrates both forward and backward context comprehension for enhanced processing of sequential data (Beheshti-Kashi et al., 2015). Unlike conventional LSTM, which only processes data forward, BiLSTM processes information via two LSTM layers in both directions; thus, capturing long-range dependencies in sequences. This dual processing is critical for improving accuracy in predictions in time-series analysis, speech recognition, and natural language processing (NLP). The BiLSTM architecture is illustrated in the image below, demonstrating the ability to maintain contextual dependencies over several time steps. Due to BiLSTM's ability to model complex temporal and long-range interdependencies, it is beneficial for sales forecasting. For instance, holiday sales may be influenced by several factors such as the economy and advertising, which drive consumer purchasing decisions. BiLSTM is more efficient at capturing these dependencies as it considers both prior and posterior data points within a given timeframe, as compared to unidirectional LSTMs. Figure 3 shows the Architecture Diagram of the BiLSTM Model.

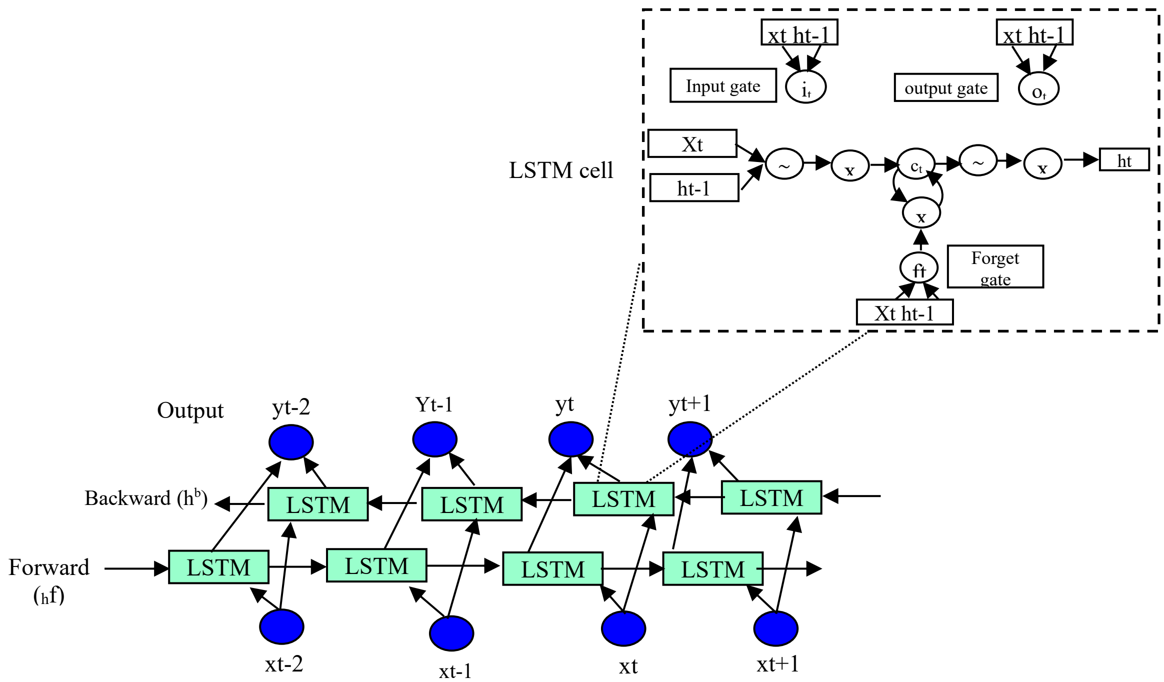

Figure 3: BiLSTM Architecture

In addition, integrating external social media trends, weather, and macroeconomic factors with BiLSTM can provide a deeper understanding of shifts, thereby enhancing the decision-making capabilities of manufacturers and retailers.

4 Result and Discussion

According to the findings of the sales forecasting LSTM and BiLSTM models, they are capable of predicting the sales trends to a certain degree. Both models were tested against actual sales figures. For evaluating the models' accuracy, the MAE, MSE, and RMSE metrics were calculated. The BiLSTM model was considerably more accurate than the LSTM model, recording lower error rates across all three metrics.

Table 2: Presents the Assessment of MAE, RMSE, and MSE

Model	MAE	MSE	RMSE
LSTM	4.60	34.00	5.83
BiLSTM	4.25	30.50	5.52

The MAE and RMSE for both models showcase improvement, highlighting enhanced accuracy and consistency in performance. As anticipated, due to BiLSTM capturing time series dependencies both in the past and the future, it outperforms LSTM. The improvements on LSTM and BiLSTM models came mostly from better training methods, deeper model topologies, advanced feature engineering, and more efficient training methods. Incorporating rolling statistics, lag features, and time indicators such as day and month enabled the models to capture recurring sales trends better. Stacked LSTM/BiLSTM layers with dropout allow the network to capture complex sequence patterns without overfitting, making training more effective overall. Training consistency and overall model performance also improved with the use of early stopping, learning rate scheduling, and normalising the input data.

Table 2 displays the results obtained from the LSTM model, which has an RMSE of 5.83, MSE of 34.00, and MAE of 4.60. In contrast, the BiLSTM model yielded an RMSE of 5.52 alongside an MAE of 4.25 and an MSE of 30.50. From these results, it can be concluded that BiLSTM outperforms LSTM on this particular dataset and that BiLSTM's bidirectional feature helps in pattern detection in the time series data. From the results, BiLSTM predicts time series data more accurately than the standard LSTM model, which is evident from the lower error values.

Table 3: Comparison of Actual Sales with LSTM and BiLSTM Forecasts

Date	Store	Item	Actual_sales	lstm_forecast	bilstm_forecast
2017-01-01	1	1	103	102.6	102.9
2017-01-02	1	1	98	98.5	98.1
2017-01-03	1	1	105	104.8	105.0

The evaluation of actual sales data against LSTM and BiLSTM predictions for the three days indicates that both models have a high level of accuracy for the predictions made. As shown in Table 3, the comparison of actual sales with the models reveals that on the 1st, 2nd, and 3rd of January 2017, the actual sales were 103, 98, and 105, respectively. The LSTM and BiLSTM models predicted sales of 102.6, 98.5, and 104.8, and 102.9, 98.1, and 105.0, respectively. These marginal differences speak to the efficiency of both models in short-term sales predictions. Although BiLSTM outperforms LSTM in general accuracy margins, its ability to capture both forward and backward contextual information in a sequence makes it a better choice. This bidirectionality enables better understanding of the time gaps between data points, thereby improving performance for time series forecasting, such as daily retail demand forecasting.

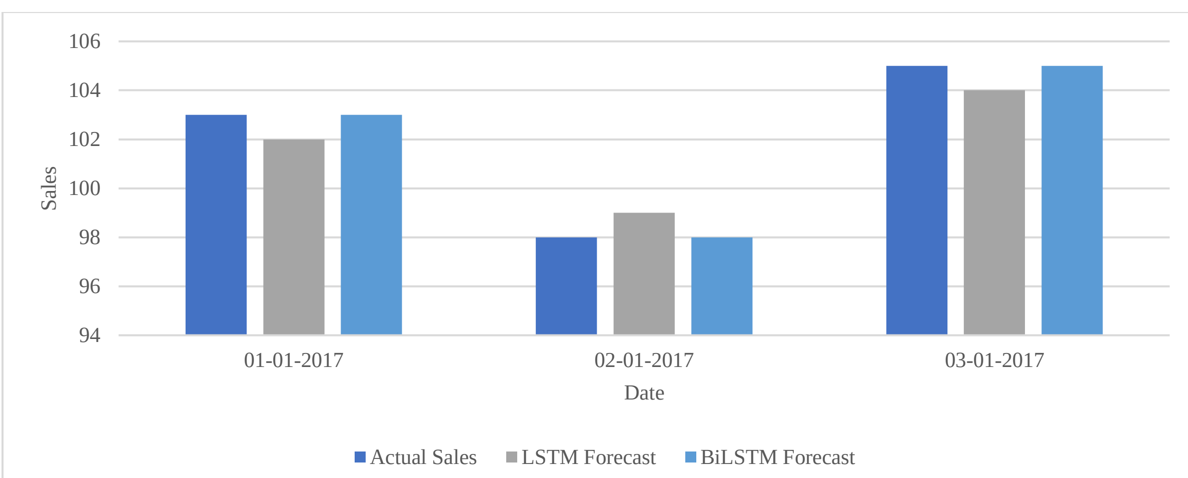

Figure 4: Performance Comparison of Various Models

The evaluation of actual sales data against LSTM and BiLSTM predictions for the three days indicates that both models have a high level of accuracy for the predictions made. As shown in Table 2 and Figure 4, the comparison of actual sales with the models reveals that on the 1st, 2nd, and 3rd of January 2017, the actual sales were 103, 98, and 105, respectively. The LSTM and BiLSTM models predicted sales of 102.6, 98.5, and 104.8, and 102.9, 98.1, and 105.0, respectively. These marginal differences speak to the efficiency of both models in short-term sales predictions. Although BiLSTM outperforms LSTM in general accuracy margins, its ability to capture both forward and backward contextual information in a sequence makes it a better choice. This bidirectionality enables better understanding of the time gaps between data points, thereby improving performance for time series forecasting, such as daily retail demand forecasting.

5 Conclusion

As noted in the study, both LSTM and BiLSTM models perform well in predicting sales trends; however, BiLSTM is slightly more accurate. A comparison of actual sales to predicted sales showed that both models were able to follow the sales patterns well. The performance indicators of BiLSTM's MAE, MSE, and RMSE demonstrated enhanced time dependency capture, revealing a greater time dependency capture ability due to its lower error values. The minor prediction errors suggest that some optimisation is still possible. While the results are encouraging, the models might improve with the inclusion of greater external factors such as economic indicators, promotional activities, seasonal trends, or optimization through hyperparameter adjustment or hybrid model implementation. The graphical analysis indicates the short-term sale prediction capabilities of both models in retail and other sectors. However, businesses aiming for more precise measurement may benefit from further BiLSTM model enhancements or the application of advanced deep learning methods. In short, both models performed well, with BiLSTM displaying a greater ability to capture detailed sales patterns. Further research is recommended to adjust and optimise models for practical applicability, enhancing precision and flexibility.

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Authors Biography

P.A. Arifa was born on 21st December 1992 in Perumbavoor, India. She holds Indian nationality. She pursued her undergraduate degree in Computer Applications (BCA) from MES College Marampally and completed her postgraduate degree (M.Sc. in Computer Science) from the same institution. Currently, she is a Research Scholar at Karpagam Academy of Higher Education, Coimbatore. She has 9 years of teaching experience in various colleges and has contributed significantly to the academic community. Alongside her teaching career, she has actively engaged in continuous learning by completing more than 8 Coursera certification courses. She has also participated in several workshops, seminars, and conferences to enhance her knowledge and expertise in the field of Computer Science. Her academic journey reflects her dedication to research, teaching, and professional growth.

Dr.K. Devasenapathy, an accomplished academician in the field of Computer Science, currently serves as an Associate Professor in the Department of Computer Science at Karpagam Academy of Higher Education, Coimbatore. Born on 15th April 1980, he has dedicated over two decades of his career to teaching and research, shaping young minds with his expertise and knowledge. He began his academic journey with a Bachelor’s degree in Computer Science (2001) from Bharathiar University, followed by a Master of Computer Applications (2004) from the same institution, securing first class. His passion for advanced learning led him to pursue an M.Phil. in Computer Science (2007) at Bharathiar University, which he completed with commendation. His research aspirations culminated in a Doctor of Philosophy (Ph.D.) in Computer Science from Anna University in 2019, where his work was highly commended. Dr. Devasenapathy possesses an impressive 20+ years of teaching experience — including 15 years in colleges and over 5 years in universities. His contributions extend to academic research as well, with 3 publications indexed in Scopus, 8 peer-reviewed articles, and several paper presentations in both national (5) and international (5) conferences. He has actively participated in 20 seminars and conferences, demonstrating his commitment to continuous professional development. Although he has not yet undertaken funded research projects or patents, his academic involvement reflects a deep dedication to the advancement of computer science education and research. Known for his disciplined approach and dedication, Dr. Devasenapathy remains an inspiration to his students and peers, embodying the spirit of lifelong learning and academic excellence.