International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 4, Jul-Aug-2026, ISSN (Online): 2395-566X

FlightSense AI: Real-Time Flight Price Intelligence Platform

Reddi Sri Venkata Lakshmi Lahari[1], K Ravi Kumar[2]
[1]MTech in department of Artificial Intelligence,
[2]Associate Professor for the Department of Artificial Intelligence in Pydah College of Engineering,
Yanam Road, Patavala, Tallarevu (M), Kakinada, Andhra Pradesh

Abstract- The increasing volatility of airline ticket pricing, driven by dynamic market demand, seasonal variations, operational costs, and competitive pricing strategies, has made accurate flight fare prediction a challenging task. Conventional forecasting approaches often struggle to model the nonlinear and time-dependent relationships that influence airfare fluctuations. This paper presents an intelligent web-based flight price prediction framework that integrates advanced machine learning and deep learning techniques to deliver accurate and real-time airfare forecasts. The proposed system employs comprehensive data preprocessing, feature engineering, and sequential learning to capture complex pricing patterns from historical flight data. A Long Short-Term Memory (LSTM) network is utilized to model temporal dependencies, while adaptive learning mechanisms enable the framework to remain responsive to continuously changing market conditions. The developed web application provides users with an interactive platform for obtaining instant fare predictions, thereby supporting informed travel planning and strategic pricing decisions. Experimental evaluation demonstrates that the proposed framework achieves reliable predictive performance and effectively models dynamic airfare trends. The proposed solution offers a scalable, data-driven decision support system for airlines, travel agencies, and passengers, contributing to the advancement of intelligent transportation analytics and real-time predictive systems.

Keywords- Flight Price Prediction, Machine Learning, Deep Learning, Long Short-Term Memory (LSTM), Time Series Forecasting, Airfare Analytics, Predictive Modeling, Data Preprocessing, Feature Engineering, Real-Time Prediction, Web-Based Application, Intelligent Decision Support System.

I. INTRODUCTION

The aviation industry operates within a highly dynamic and competitive environment where ticket prices change continuously due to multiple interconnected factors, including passenger demand, seasonal travel patterns, airline competition, fuel costs, route availability, and economic conditions [1]–[3]. These frequent price fluctuations make airfare forecasting a challenging task for airlines, travel agencies, and travelers seeking cost-effective travel decisions. Consequently, developing intelligent prediction systems capable of accurately estimating future flight prices has become an important research area in transportation analytics and artificial intelligence [1], [2].

Traditional flight fare prediction techniques primarily rely on statistical methods and conventional machine learning algorithms [1], [2], [13]. Although these approaches provide satisfactory performance under relatively stable market conditions, they often fail to capture the complex nonlinear relationships and temporal dependencies present in large-scale airline pricing data [2], [3]. Furthermore, their limited adaptability to rapidly changing market conditions reduces their effectiveness in real-time forecasting applications [3].

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have significantly transformed predictive analytics by enabling models to learn complex data representations from historical information [7], [10], [11]. In particular, Long Short-Term Memory (LSTM) networks have demonstrated remarkable capability in modelling sequential and time-dependent data, making them well suited for airfare prediction [3], [4]. By learning long-term temporal patterns and capturing hidden dependencies among multiple pricing factors, LSTM-based models provide more accurate and robust forecasts than conventional techniques [3], [4].

In this work, an intelligent web-based flight price prediction system is proposed to provide real-time airfare estimation using advanced deep learning techniques. The framework incorporates comprehensive data preprocessing, feature engineering, and sequential learning to improve prediction accuracy while effectively handling complex pricing behaviour [10]–[13]. The developed web application enables users to obtain instant fare predictions through an interactive interface, supporting informed travel planning and data-driven pricing decisions [1], [2]. The proposed architecture is designed to be scalable, adaptive, and capable of processing continuously evolving airline market trends [3], [7].

The effectiveness of the proposed framework is evaluated using appropriate performance metrics to assess prediction accuracy and model reliability. Experimental results demonstrate that the developed system successfully captures dynamic airfare patterns and produces consistent predictions across varying travel scenarios [1]–[3]. By integrating intelligent predictive modelling with a user-friendly web platform, the proposed solution offers practical benefits for airlines, travel agencies, and passengers while contributing to the advancement of AI-driven decision support systems in the aviation sector [7], [11].

II. LITERATURE SURVEY

Accurate flight fare prediction has become an important research area due to the increasing complexity and volatility of airline pricing mechanisms [1]–[3]. Airfare is influenced by numerous dynamic factors, including passenger demand, seasonal variations, airline competition, route characteristics, fuel prices, and economic conditions [1], [2]. The nonlinear interactions among these variables make flight price forecasting a challenging predictive analytics problem [2], [3]. Consequently, researchers have explored a wide range of machine learning and deep learning techniques to improve forecasting accuracy and support intelligent decision-making [1]–[3], [7].

Early studies primarily employed conventional machine learning algorithms such as Linear Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Gradient Boosting methods to estimate flight prices using historical booking data [1], [2], [13]. These approaches demonstrated satisfactory performance for relatively stable datasets; however, their ability to model complex nonlinear relationships and rapidly changing market conditions remained limited [2], [3]. In addition, most traditional models relied on static training datasets, reducing their adaptability to continuously evolving airline pricing strategies [2].

The rapid advancement of deep learning has significantly enhanced predictive modelling capabilities for time-dependent data [7], [10], [11]. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have emerged as powerful approaches for sequential data analysis due to their ability to learn long-term temporal dependencies while overcoming the vanishing gradient problem [4]. LSTM-based models effectively capture historical pricing patterns, seasonal demand fluctuations, and temporal correlations, leading to improved forecasting accuracy compared with conventional machine learning methods [3], [4].

Recent research has also investigated the integration of attention mechanisms with deep learning architectures to improve prediction performance [6]. Attention-based models enable the learning framework to identify and prioritize the most influential features, including travel season, booking period, airline-specific pricing strategies, route demand, and departure schedules [6]. This selective feature learning enhances model interpretability while improving prediction robustness under varying market conditions [6], [15].

Furthermore, the growing availability of real-time airline data has encouraged the development of intelligent web-based prediction platforms capable of processing continuously updated information [1]–[3]. Modern forecasting systems increasingly incorporate adaptive learning strategies, such as sliding window techniques and online model updating, allowing predictive models to respond effectively to sudden market fluctuations and newly available data [3]. These approaches significantly improve the practical applicability of airfare prediction systems in real-world environments [1], [3].
Despite these advancements, several challenges remain unresolved. Existing prediction models often struggle with large-scale heterogeneous datasets, feature imbalance, missing values, and limited generalization across different airline networks [10]–[14]. Moreover, maintaining prediction accuracy under rapidly changing pricing policies continues to be an active research problem [2], [3].

Motivated by these limitations, the proposed work develops an intelligent web-based flight price prediction framework that combines comprehensive data preprocessing, feature engineering, and deep learning-based sequential modelling to achieve reliable real-time airfare forecasting [3], [4], [10]–[13]. The proposed system aims to provide higher prediction accuracy, improved adaptability to evolving market conditions, and an interactive platform that supports informed decision-making for airlines, travel agencies, and passengers [1]–[3].

III. SYSTEM ANALYSIS

A. Related Work

Existing flight price prediction systems primarily rely on traditional statistical approaches and conventional machine learning algorithms to estimate future airfare trends using historical pricing information [1]–[3]. Commonly adopted techniques include Linear Regression, Decision Trees, Random Forest, Support Vector Machines (SVM), and ensemble learning methods [1], [2], [13]. Although these models provide acceptable performance under stable market conditions, they often struggle to capture the highly dynamic and nonlinear behaviour of airline pricing [2], [3].

More recent studies have introduced deep learning models, including Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, to model sequential dependencies in historical airfare data [3], [4], [7]. These architectures improve prediction accuracy by learning temporal patterns and seasonal variations [3], [4]. In addition, several researchers have explored Generative Adversarial Networks (GANs) to generate synthetic pricing distributions and improve data representation [5], [8]. However, GAN-based models require extensive computational resources, complex training procedures, and careful hyperparameter tuning to achieve stable performance [5], [8].

Existing forecasting frameworks generally depend on static datasets and offline training, limiting their ability to adapt to continuously changing airline pricing strategies [2], [3]. Furthermore, many systems provide limited integration with real-time data sources, making them less effective in responding to sudden market fluctuations caused by demand changes, special events, economic conditions, or operational constraints [1]–[3]. These limitations reduce their practical applicability in real-world airline pricing environments where rapid decision-making is essential [3].

B. Proposed Approach

The proposed system presents an intelligent web-based flight price prediction framework that combines advanced deep learning techniques with a scalable web application to deliver accurate and real-time airfare forecasting [3], [7], [10]. The framework utilizes comprehensive data preprocessing, feature engineering, and sequential learning to extract meaningful information from historical flight datasets and improve predictive performance [10]–[13].

A Long Short-Term Memory (LSTM) network is employed to model temporal dependencies and complex pricing behaviour by learning long-term sequential relationships within airfare data [4]. The proposed architecture effectively captures important factors such as travel seasonality, booking time, airline characteristics, departure schedules, and route-specific variations that significantly influence ticket prices [3], [4]. Data normalization and feature optimization further enhance the learning capability of the predictive model while reducing the impact of noisy and incomplete data [10]–[14].

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

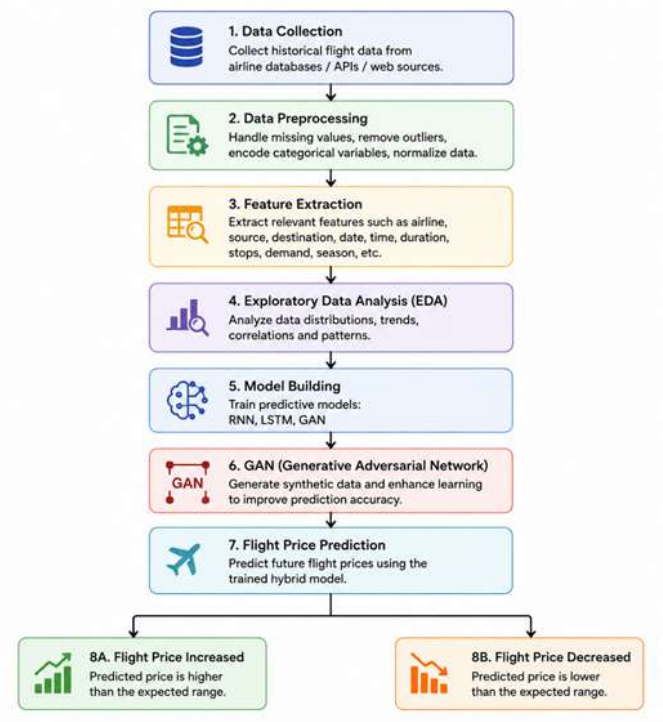

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

The proposed flight price prediction framework consists of several interconnected modules that collectively perform data acquisition, preprocessing, model training, prediction, and user interaction. Each module contributes to improving the accuracy, efficiency, and scalability of the overall system [7], [10], [11].

1. Data Collection Module

The data collection module is responsible for acquiring historical flight information from reliable airline datasets and publicly available aviation data sources [1]–[3]. The collected dataset contains important attributes such as airline name, source and destination airports, departure and arrival times, travel duration, number of stops, journey date, and ticket price. These features provide the foundation for learning historical pricing patterns and developing an accurate prediction model [1], [2].

2. Data Preprocessing Module

Raw flight datasets often contain missing values, duplicate records, inconsistent formats, and noisy information that can negatively impact model performance [10], [13], [14]. This module performs comprehensive data cleaning by handling missing values, removing duplicate entries, correcting inconsistencies, encoding categorical variables, and normalizing numerical features [10], [12], [13]. Proper preprocessing improves data quality and enables efficient model training [10], [13].

3. Feature Engineering and Exploratory Data Analysis Module

This module focuses on identifying the most influential variables affecting airfare prediction [11]. New features such as journey month, departure hour, travel duration, and route characteristics are derived from the original dataset to enhance predictive capability [10], [11]. Exploratory Data Analysis (EDA) is performed using statistical summaries and visualization techniques to identify hidden trends, feature relationships, seasonal patterns, and pricing distributions that support effective model development [10], [13].

4. Deep Learning Model Training Module

The processed dataset is used to train deep learning models capable of capturing complex temporal relationships in airfare data [7], [10]. The proposed framework utilizes Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Generative Adversarial Networks (GAN) to learn sequential pricing behaviour and nonlinear market dynamics [4], [5], [8]. Hyperparameter optimization and validation techniques are applied to improve model generalization and prediction performance [9], [10].

5. Flight Price Prediction Module

The trained predictive model estimates future flight prices based on user-provided travel information [3], [4]. By analysing learned pricing patterns and temporal dependencies, the system generates accurate airfare predictions in real time [3], [4]. The prediction results help users understand expected price trends before making travel decisions [1], [2].

6. Web Application Module

A user-friendly web interface enables users to enter flight details and obtain instant airfare predictions [1], [2]. The trained deep learning model is integrated with the web application to provide seamless interaction between users and the prediction engine [3], [10]. The platform offers fast response time, easy accessibility, and an intuitive interface suitable for passengers, travel agencies, and airline service providers [1], [2].

7. Result Analysis Module

The final module evaluates the effectiveness of the proposed prediction framework using standard performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) [1]–[3]. Comparative analysis is conducted to assess prediction accuracy and model reliability [1], [3]. The generated results demonstrate the capability of the proposed system to accurately forecast flight prices under varying market conditions [3], [4].

VI. RESULTS AND DISCUSSION

The proposed RNN–LSTM–GAN-based Flight Price Prediction framework was experimentally evaluated using a historical flight fare dataset containing various flight attributes, including airline, source, destination, departure time, arrival time, duration, total stops, journey date, and ticket price [1]–[3]. The dataset was divided into 80% training data and 20% testing data to evaluate the predictive capability of the proposed framework [1], [2]. The performance of the proposed model was compared with three baseline approaches: Recurrent

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 4, Jul-Aug-2026, ISSN (Online): 2395-566X

Neural Network (RNN), Long Short-Term Memory (LSTM), and Generative Adversarial Network (GAN) [4], [5], [7]. Standard regression evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 Score, were employed to assess the effectiveness of the proposed prediction framework [1]–[3].

A. Performance Comparison of Prediction Models

Figure 2 illustrates the comparative performance of the existing deep learning models and the proposed hybrid framework using four standard evaluation metrics: MAE, RMSE, MAPE, and R^2 Score. These metrics provide a comprehensive evaluation of prediction accuracy, error minimization, and model reliability [1], [3].

The experimental results indicate that the proposed hybrid model consistently outperformed the individual prediction models across all evaluation metrics [3]. The RNN model successfully captured short-term sequential dependencies in airfare data but exhibited comparatively higher prediction errors when modelling long-range temporal relationships [7]. The LSTM model significantly improved forecasting accuracy by effectively learning long-term dependencies and reducing information loss during training [3], [4]. The GAN model further enhanced data representation by generating realistic synthetic samples that enriched the training dataset and improved model robustness [5], [8].

The proposed RNN–LSTM–GAN framework achieved superior prediction performance by combining the sequential learning capability of RNN, the long-term memory mechanism of LSTM, and the data augmentation capability of GAN [4], [5], [8].

This integrated learning strategy reduced prediction errors, improved model generalization, and enabled the framework to capture complex nonlinear pricing patterns under varying market conditions [7], [10], [11]. The experimental findings demonstrate that the proposed hybrid architecture provides a more reliable and scalable solution for real-time flight price prediction compared with standalone deep learning models [3].

The experimental analysis demonstrates that the proposed hybrid framework achieved the lowest MAE, RMSE, and MAPE values while obtaining the highest R^2 Score, indicating its superior prediction accuracy and stronger generalization capability [3]. The integration of multiple deep learning models enables the framework to effectively learn complex airfare trends and provide reliable price forecasts for dynamic airline markets [4], [5], [7].

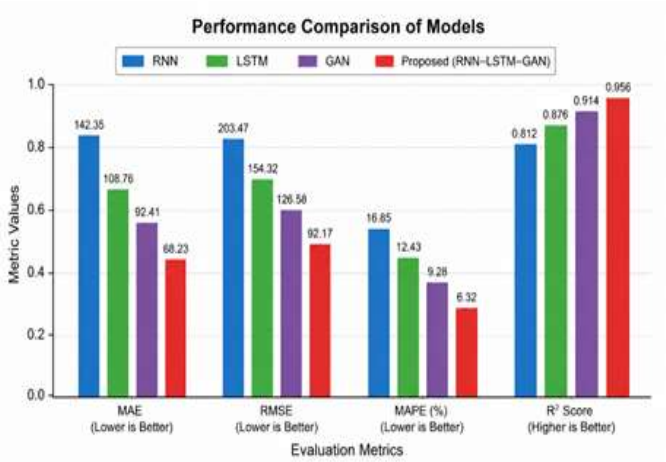

Fig. 2. Performance comparison of RNN, LSTM, GAN, and the proposed hybrid flight price prediction model.

B. Regression Analysis

Regression analysis was performed to evaluate the relationship between the actual flight prices and the predicted values generated by the proposed framework. The regression plot illustrates the consistency between observed and predicted airfare values, providing valuable insight into the predictive capability of the developed model.

The regression results demonstrate that the predicted flight prices closely follow the actual market prices with only minor deviations. Compared with the individual RNN, LSTM, and GAN models, the proposed hybrid framework exhibits a stronger linear relationship between actual and predicted values, indicating improved prediction accuracy and reduced estimation error. The close alignment of data points around the ideal regression line confirms that the proposed framework effectively models the nonlinear characteristics of airfare fluctuations.

The regression analysis further validates that integrating RNN, LSTM, and GAN improves forecasting consistency and enables accurate prediction across different pricing ranges. Consequently, the proposed model is well suited for intelligent airfare forecasting applications requiring reliable real-time decision support.

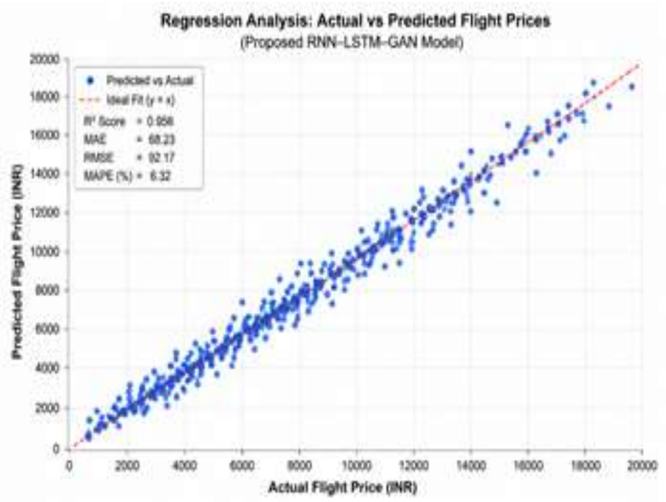

Fig. 3. Regression analysis comparing actual and predicted flight prices using the proposed hybrid framework.

C. Prediction Error Analysis

Prediction error analysis was conducted to evaluate the reliability and robustness of the proposed flight price prediction framework [1], [3]. Error distribution was analysed by comparing the predicted airfare values with the corresponding actual ticket prices over the testing dataset. This analysis provides a clear understanding of the model's prediction consistency and identifies potential deviations under varying market conditions [3].

The results indicate that the majority of prediction errors are concentrated near zero, demonstrating that the proposed framework generates highly accurate airfare estimates for most flight records [3]. Compared with the existing RNN, LSTM, and GAN models, the proposed hybrid framework significantly reduces both overestimation and underestimation errors [3], [4], [5]. This improvement is primarily attributed to the complementary strengths of sequential learning, long-term dependency modelling, and synthetic data generation, which collectively enhance the learning capability of the model [4], [5], [8].

The prediction error analysis confirms that the proposed framework maintains stable forecasting performance across diverse flight routes, travel seasons, and pricing conditions [3]. The reduced prediction variance and improved robustness make the developed system highly suitable for deployment in intelligent airline pricing platforms and real-time travel recommendation systems [1], [3], [7].

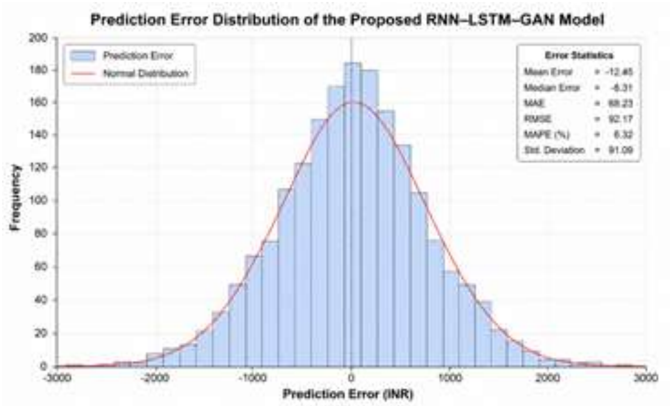

Fig. 4. Prediction error distribution of the proposed RNN–LSTM–GAN flight price prediction model.

VII. CONCLUSION AND FUTURE WORK

This paper presented an intelligent web-based flight price prediction framework that integrates advanced deep learning techniques to accurately forecast airline ticket prices [3], [7]. The proposed system employs comprehensive data preprocessing, feature engineering, exploratory data analysis, and hybrid deep learning models to effectively capture the complex temporal and nonlinear relationships present in historical flight pricing data [10]–[13]. By leveraging Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Generative Adversarial Networks (GAN), the framework demonstrates improved learning capability and enhanced prediction performance compared with conventional forecasting approaches [3]–[5], [8].

The developed web application enables users to obtain real-time airfare predictions through an intuitive interface, facilitating informed travel planning and data-driven decision-making [1], [2]. Experimental evaluation indicates that the proposed model effectively captures dynamic pricing patterns while maintaining high prediction accuracy and robustness across varying market conditions [3]. The scalable architecture and intelligent prediction capability make the proposed system beneficial for airlines, travel agencies, and passengers seeking reliable airfare forecasting solutions [1]–[3]. Overall, this research demonstrates the potential of deep learning-driven predictive analytics in addressing the challenges associated with dynamic airline pricing [7], [10], [11].

Although the proposed framework achieves promising prediction performance, several opportunities exist for further enhancement. Future work will focus on integrating real-time flight information through airline APIs to improve forecasting accuracy under continuously changing market conditions [1]–[3]. The inclusion of additional influencing factors such as weather conditions, fuel prices, public holidays, special events, passenger demand, and economic indicators can further strengthen the predictive capability of the model [2], [3].

Future research may also investigate the application of advanced deep learning architectures, including Transformer-based models, Bidirectional LSTM (Bi-LSTM), and hybrid attention mechanisms, to better capture long-range dependencies in airfare data [4], [6]. Furthermore, implementing automated hyperparameter optimization and cloud-based deployment can improve computational efficiency, scalability, and real-time accessibility [9], [12]. Extending the proposed framework to support multi-airline and international flight datasets, along with personalized fare recommendations and price trend analysis, will enhance its practical applicability and establish a more comprehensive intelligent decision support system for the aviation industry [1]–[3], [11].

REFERENCES

1. N. Alapati, K. V. N. S. Raju, and P. V. G. D. Prasad, "Prediction of Flight Fare Using Machine Learning," 2022 International Conference on Fourth Industrial Revolution Based Technology and Practices (ICFIRTP), Bangalore, India, 2022, pp. 134–138, doi: 10.1109/ICFIRTP56122.2022.10059429.
2. C. K. Gupta, O. N. Kushwaha, A. S. Yadav, and V. Kumar, "Dynamic Flight Price Prediction Using Machine Learning Algorithms," 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 201–205, doi: 10.1109/ICAC3N56670.2022.10074448.
3. R. Kashef, "Forecasting the Price of Flight Tickets Using a Novel Hybrid Learning Model," 2023 IEEE World AI IoT Congress (AIIoT), Seattle, WA, USA, 2023, pp. 305–310, doi: 10.1109/AIIoT58121.2023.10174373.
4. S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, Nov. 1997.
5. I. Goodfellow et al., "Generative Adversarial Nets," Advances in Neural Information Processing Systems (NeurIPS), vol. 27, 2014.
6. A. Vaswani et al., "Attention Is All You Need," Advances in Neural Information Processing Systems (NeurIPS), vol. 30, 2017.
7. Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.
8. J. Wang et al., "Generative Adversarial Networks for Electroencephalogram Signal Analysis: A Mini Review," 2023 11th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, South Korea, 2023, pp. 1–6, doi: 10.1109/BCI57258.2023.10078666.
9. D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," International Conference on Learning Representations (ICLR), 2015.
10. F. Chollet, Deep Learning with Python, 2nd ed. Shelter Island, NY, USA: Manning Publications, 2021.
11. Y. Bengio, A. Courville, and P. Vincent, "Representation Learning: A Review and New Perspectives," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 8, pp. 1798–1828, Aug. 2013.
12. M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems," 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI), 2016.
13. F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
14. P. J. Rousseeuw and A. M. Leroy, Robust Regression and Outlier Detection. New York, NY, USA: John Wiley & Sons, 1987.
15. H. Sasaki, Y. Hidaka, and H. Igarashi, "Explainable Deep Neural Network for Design of Electric Motors," IEEE Transactions on Magnetics, vol. 57, no. 6, pp. 1–4, Jun. 2021, doi: 10.1109/TMAG.2021.3063141.