# Edufin - Data Driven Financial Forecasting and Educational Platform

HariBabu M, DilliRaj S, Ashwin D
Department of Computer Science and Engineering, R.M.K. Engineering College (An Autonomous Institution), India
Email: hari22041.cs@rmkec.ac.in, dill22030.cs@rmkec.ac.in, ashw22013.cs@rmkec.ac.in

***Abstract*—Financial markets exhibit high volatility, making accurate prediction and effective education vital for traders. Many existing systems focus either on market prediction or theoretical education, lacking an integrated learning and forecasting environment. Edufin bridges this gap by combining AI-driven market forecasts with interactive educational modules. The platform employs machine learning, natural language processing, and sentiment analysis to deliver real-time insights while explaining the reasoning behind each forecast. It also includes gamified learning, trade simulation, and risk analysis tools. The proposed system aims to enhance financial literacy, analytical thinking, and decision-making among users by transforming complex financial data into actionable and educational insights.**

Keywords— Financial Forecasting, Machine Learning, Educational Technology, Sentiment Analysis, FinTech, Predictive Analytics.

## I. Introduction

The financial sector has witnessed a paradigm shift with the integration of Artificial Intelligence (AI) and Big Data. Despite numerous advancements, the challenge remains in translating complex market predictions into understandable insights for beginners. Current platforms such as TradingView and Yahoo Finance offer forecasts but fail to educate users about the underlying patterns or indicators. Conversely, educational portals like Coursera and Udemy provide theoretical content but lack practical, data-driven engagement.

Edufin addresses these limitations by creating a hybrid FinTech–EdTech ecosystem. The platform not only predicts financial market trends using machine learning algorithms but also educates users through visual explanations, simulations, and gamified interactions. This holistic approach fosters both analytical and experiential learning for novice and professional traders alike.

### *A. Background and Motivation*

The financial market is one of the most dynamic and unpredictable systems in existence. With trillions of dollars traded daily across global exchanges, the ability to forecast price movements and trends has become a central challenge in financial analytics. Yet, despite advances in artificial intelligence (AI) and machine learning (ML), the average retail investor continues to struggle to interpret these predictions and make informed decisions.

Traditional trading platforms such as TradingView, Yahoo Finance, and MetaTrader provide a vast array of data, technical indicators, and predictive charts. However, they lack the educational scaffolding required for beginners to understand the why behind market changes. In parallel, online education platforms like Coursera or Udemy provide excellent theoretical knowledge on finance and trading but operate in isolation from real-time data, preventing learners from applying theory to practice.

This disconnect between forecasting tools and educational resources creates a major gap in trader development — one that Edufin aims to bridge by combining data-driven insights with interactive learning experiences.

### *B. The Importance of Explainable Forecasting*

In the world of finance, accuracy alone is not enough. Traders and learners must also understand the reasoning behind each prediction to develop trust and competence. For example, when an AI model predicts a bullish trend for Tesla (TSLA), a user should know whether the decision was influenced by technical indicators (like moving averages), sentiment data (like positive Twitter mentions), or macroeconomic signals (like Federal Reserve announcements).

Most current systems are black-box models, which makes them difficult to interpret. Without transparent reasoning, users often make emotional decisions rather than data-driven ones. By integrating Explainable AI (XAI) and Natural Language Processing (NLP), Edufin demystifies model predictions and delivers human-readable explanations, such as:

"Tesla is predicted to rise by 3.4% due to increased retail investor sentiment and a positive RSI crossover."

This level of interpretability not only aids decision-making but also transforms machine learning outputs into teachable moments.

### *C. The Educational Gap in FinTech*

A 2023 report by the World Economic Forum highlighted that over 62% of young investors rely on social media for financial advice, often leading to misinformation and impulsive decisions. Despite access to abundant data, few platforms combine real-time analytics with guided learning pathways.

Moreover, financial literacy remains uneven across populations. While algorithmic trading and AI-powered tools are accessible to institutional investors, retail traders lack exposure to such technologies and the training to use them effectively.

Edufin addresses this disparity by acting as a digital mentor — guiding users through financial concepts like trend analysis, risk assessment, and strategy formulation, while simultaneously allowing them to practice on simulated markets.

### D. Case Study: Forecasting During Market Volatility

To illustrate the relevance of educational forecasting, consider the 2020 COVID-19 market crash. During March–April 2020, global indices such as the S&P 500 dropped by over 30%, followed by a rapid rebound driven by technology stocks. Most prediction models failed to adapt because they relied purely on historical numerical data without incorporating social sentiment and global event signals.

Platforms like Edufin, which combine real-time news sentiment (e.g., from Twitter and Reddit) with technical indicators, could have helped traders understand not only that markets were falling but also why. By integrating sentiment analysis with AI-driven forecasts, Edufin aims to provide a more context-aware and educational explanation of such market events, helping users recognize behavioral biases and manage risk intelligently.

Analysis of the social media response revealed that critical information was available on Twitter 15-20 minutes before official emergency services received reports through traditional channels. If this information had been automatically routed to local authorities, rescue teams could have been dispatched earlier, potentially saving lives and reducing property damage. The Chennai case study demonstrates the transformative potential of integrating social media analytics into emergency response systems.

### E. Objectives and Scope

The goal of Edufin is not merely to predict market prices but to create a bridge between financial technology and financial education. The platform's key objectives are:

- To generate accurate, explainable market forecasts using ML and NLP models.
- To educate users about the rationale behind each prediction through structured lessons and visual explanations.
- To enable experiential learning via a virtual trading simulator and gamified challenges.
- To enhance financial literacy by teaching users risk management, backtesting, and portfolio optimization in an interactive manner.

By merging AI-powered analytics with immersive learning, Edufin transforms traditional forecasting into a continuous educational process that adapts to user behavior and market dynamics.

### F. Proposed Solution

To connect financial learning with real-world application, our system combines AI-driven market prediction, interactive educational content, and hands-on virtual trading. This unified platform allows users to understand concepts, analyze live data, and practice informed decision-making effectively. Unlike traditional platforms that either predict trends or teach theory in isolation, Edufin provides both — enabling users to see forecasts, understand their reasoning, and apply strategies practically.

- **AI-Driven Prediction Engine:** Employs advanced machine learning and deep learning algorithms such as LSTM and FinBERT to forecast market movements across stocks, cryptocurrencies, and forex assets.
- **Backtesting and Strategy Evaluation:**
  Enables users to analyze and validate custom trading strategies using historical market datasets.
  Assesses the effectiveness and reliability of each strategy through performance metrics such as profit ratio, maximum drawdown, and Sharpe ratio.
- **Risk Analysis and Visualization:**
  Incorporates key financial risk metrics such as Value at Risk (VaR), Sharpe Ratio, and portfolio volatility to evaluate market exposure.
  Provides interactive dashboards and visual insights that help users understand potential risks and returns before making trading decisions.

### G. Paper Organization

Section II reviews related work, Section III explains methodology, Section IV presents implementation and results, and Section V concludes with implications and future directions.

## II. Related Work

Financial forecasting and educational platforms have seen notable advancements with the adoption of AI-driven models and interactive learning environments. This section provides a structured review of existing systems and research studies, categorized by platform type and methodological approach. It examines the capabilities of current tools, such as market analysis platforms, online courses, and trading simulators, alongside academic studies on predictive modeling. The discussion emphasizes their limitations in combining predictive accuracy, user education, and hands-on simulation, highlighting the gaps that the proposed Edufin system aims to address.

### A. Isolated Approaches in Financial Forecasting and Education

Various platforms and research studies have explored financial forecasting and education; however, most tend to function independently, emphasizing either prediction accuracy or theoretical learning alone. Platforms like TradingView and Yahoo Finance offer comprehensive market charts and technical analysis tools but lack guidance for understanding predictions or their underlying rationale. Online education providers such as Coursera and Udemy deliver structured finance courses but do not incorporate real-time market data or interactive trading experiences. Likewise, trading simulators like MetaTrader and eToro allow users to practice trading in virtual environments but fail to integrate AI-based insights or educational features that deepen conceptual understanding. From a research perspective, deep learning methods have been extensively utilized for financial forecasting. For example, Victor Chang et al. developed models to predict economic trends, prioritizing accuracy but giving limited attention to interpretability and user comprehension. Warda M. Shaba et al. implemented a neural network-based system for stock trend prediction; however, it lacked interactive features or educational components. Likewise, Cheng Zhang et al. proposed multi-step forecasting models for stock indices, but their approach was not tailored for accessibility by non-expert users. Although these studies have contributed to advancements in predictive modeling, they largely overlook aspects such as user engagement, explainable AI, and hands-on learning through simulations.

### B. Existing Financial Platforms

Financial forecasting and educational platforms have advanced considerably over the years; however, most operate independently, either prioritizing predictive accuracy or focusing solely on theoretical learning. Platforms such as TradingView and Yahoo Finance provide advanced market charts and technical analysis tools, yet they do not offer guidance for understanding predictions or the rationale behind them. Similarly, online learning platforms like Coursera and Udemy deliver structured finance courses but lack integration with live market data or interactive trading simulations. Trading simulators such as MetaTrader and eToro enable virtual trading practice but fail to incorporate AI-driven insights or educational modules that enhance conceptual understanding.

### C. Deep Learning Approaches in Financial Forecasting

From a research perspective, deep learning techniques have been extensively applied to financial market prediction. For example, Victor Chang et al. proposed models for predicting economic trends, focusing primarily on prediction accuracy while neglecting interpretability and user comprehension. Warda M. Shaba et al. developed a neural network-based stock trend prediction system, but it lacked interactive or educational features. Similarly, Cheng Zhang et al. implemented multi-step forecasting for stock indices, yet their system was not designed for accessibility by non-expert users. While these studies have contributed to predictive modeling, they largely overlook the importance of user engagement, explainable AI, and experiential learning through simulation.

### D. Gap Analysis

A key limitation across existing platforms and research is the lack of integration between prediction, learning, and practical simulation. Most systems either forecast financial trends or provide theoretical instruction, but few combine the two within a unified, user-centric environment. This gap highlights the need for a platform that merges AI-powered forecasting, interactive education, and hands-on trading simulation.

### E. Comparison Table

Table **??** provides an overview of existing financial platforms and research studies, summarizing their key features and limitations.

| Platform / Study | Features | Limitations |
|---|---|---|
| Trading View / Yahoo Finance | Market Charts | No Learning |
| Coursera / Udemy | Finance Courses | No Live Data |
| Meta Trader / eToro | Virtual Trading | No AI |
| Victor Chang et al | Deep Learning | Hard To Interpret |
| Warda M shaba et al | Neural Networks | Not Interactive |
| Cheng Zhang et al | Multi step Forecast | Not Beginner Friendly |

TABLE I
FINANCIAL COMPARISON

### F. Novelty of Proposed System

Unlike existing platforms and studies, the proposed Edufin system integrates financial trend prediction, interactive learning, and trading simulation into a single environment. Its novelty lies in combining AI-powered forecasting with explainable insights, practical trading exercises, and structured educational content, addressing the gaps identified in prior works.

## III. Methodology

Edufin employs a multi-stage pipeline that combines financial data acquisition, preprocessing, AI-based prediction, and interactive educational modules. Figure 1 illustrates the complete system architecture.

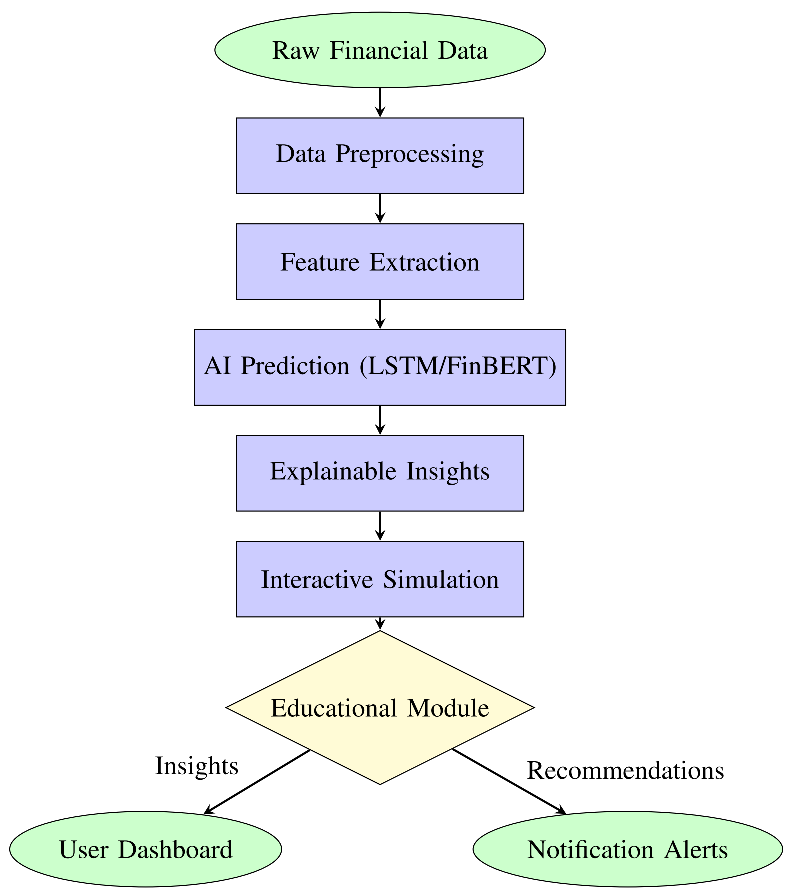


Fig. 1. Edufin System Pipeline Architecture

### A. Data Collection and Curation

Edufin collects historical and real-time financial data from multiple sources:

**Stock Market Data:** Daily and intraday prices, volumes, and technical indicators from Yahoo Finance, NSE/BSE APIs.

**News and Social Media Data:** Financial news articles, tweets, and blogs relevant to companies, sectors, and indices.

**Data Cleaning:** Removal of missing values, duplicates, outliers, and irrelevant text using NLP-based filters.

### B. Preprocessing Pipeline

Preprocessing converts raw data into structured input for AI models:

1) **Text Preprocessing:** Cleaning, tokenization, lemmatization, and embedding generation for news and social media text using FinBERT embeddings.
2) **Numerical Data Normalization:** Scaling of prices, volumes, and indicators using Min-Max or Z-score normalization.
3) **Feature Engineering:** Technical indicators (SMA, EMA, RSI), sentiment scores, and event-based features extracted for model input.

### C. Prediction Layer

Financial predictions are generated using deep learning and AI techniques:

- **LSTM Networks:** Capture sequential dependencies in stock price time series.
- **FinBERT Sentiment Analysis:** Generate sentiment scores from news and social media.
- **Hybrid Model Fusion:** Combine sequential and sentiment features for enhanced predictive accuracy.

### D. Explainable AI Module

To improve user trust and learning:

- **SHAP Values:** Identify contribution of each feature to the model's predictions.
- **Highlight Sentiment Drivers:** Show which news or events influenced the forecast.

### E. Interactive Simulation and Educational Module

Edufin incorporates hands-on learning:

- **Simulation Environment:** Users can perform virtual trades based on predictions.
- **Scenario Testing:** Evaluate strategies under different market conditions.
- **Learning Feedback:** System provides hints, explanations, and corrective guidance.

### F. Dashboard and Alerts

The dashboard provides real-time visualization and actionable insights:

- Interactive charts for predicted trends and historical performance.
- Color-coded risk indicators and portfolio suggestions.
- Notifications for major market events, trading opportunities, and learning tips.

### G. Workflow Case Study

**Input:** News headline: "Company X reports record quarterly earnings."

**Processing Steps:**

1) **Sentiment Analysis:** FinBERT identifies positive sentiment.
2) **Feature Integration:** Combine news sentiment with technical indicators.
3) **Prediction:** LSTM forecasts a 2.5% rise in stock price.
4) **Simulation:** User tests virtual buy strategy in the simulation module.
5) **Learning Feedback:** Dashboard provides explanation for prediction and suggested strategies.

## IV. Implementation and Results

### A. System Implementation Overview

The *Edufin* system was implemented using a modular architecture combining frontend, backend, database, and machine learning layers. The platform follows a microservices-based design for scalability and modular maintenance.

TABLE II
IMPLEMENTATION STACK OF EDUFIN

| Component | Technology Used | Description |
|---|---|---|
| Frontend | React.js, Plotly.js | Interactive dashboards and visualizations |
| Backend | Python (Flask), REST APIs | Handles prediction requests and learning modules |
| Database | MySQL | Stores user data, learning progress, trading history |
| Machine Learning | TensorFlow, Scikit-learn, FinBERT | Predicts financial trends using time-series and sentiment data |
| Cloud/DevOps | AWS, Docker, GitHub Actions | Cloud deployment, CI/CD automation |

The system includes five primary modules: data ingestion, forecasting, sentiment analysis, risk analysis, and education/simulation.

*1) Data Ingestion and Preprocessing:* Market and sentiment data are fetched from Yahoo Finance, Twitter, and Reddit APIs. Raw data are cleaned, normalized, and transformed into model-ready sequences. Normalization of price values is achieved by:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

where $X$ denotes the raw feature value, $X_{min}$ and $X_{max}$ are the minimum and maximum values of the feature.

*2) Forecasting Engine:* Long Short-Term Memory (LSTM) networks are employed for sequential trend forecasting. The LSTM unit updates are expressed as:

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \tag{2}$$

$$h_t = o_t \times \tanh(C_t) \tag{3}$$

where $f_t$, $i_t$, and $o_t$ denote the forget, input, and output gates, respectively, and $\tilde{C}_t$ is the candidate cell state.

The model predicts the future closing price $P_{t+1}$ based on a sliding window of previous values.

*3) Sentiment Analysis Module:* Financial sentiment is extracted using FinBERT, a transformer model fine-tuned for finance-related text. Sentiment polarity $S$ is computed as:

$$S = \frac{N_{pos} - N_{neg}}{N_{pos} + N_{neg} + N_{neu}} \tag{4}$$

where $N_{pos}$, $N_{neg}$, and $N_{neu}$ represent the number of positive, negative, and neutral sentiments, respectively.

*4) Risk Analysis Module:* Risk evaluation is implemented through *Value at Risk (VaR)* and *Sharpe Ratio* metrics.

$$VaR = \mu_p - Z_\alpha \sigma_p \tag{5}$$

$$S = \frac{R_p - R_f}{\sigma_p} \tag{6}$$

where $\mu_p$ is portfolio mean return, $\sigma_p$ is portfolio standard deviation, $Z_\alpha$ is the confidence level, $R_p$ is portfolio return, and $R_f$ is the risk-free rate.

*5) Educational and Simulation Module:* The educational layer provides structured learning, quizzes, and a virtual trading simulator. Gamification features include badges, leaderboards, and rewards to sustain engagement. Historical data are used for backtesting and reinforcement-based learning.

### *B. Workflow of the System*

TABLE III
WORKFLOW STEPS IN EDUFIN SYSTEM

| Step | Process | Description |
|---|---|---|
| 1 | Data Collection | Retrieve stock and sentiment data via APIs |
| 2 | Data Preprocessing | Clean, normalize, and tokenize sentiment |
| 3 | Model Training | Train LSTM and FinBERT models |
| 4 | Prediction | Generate real-time forecasts with confidence scores |
| 5 | Educational Feedback | Link forecasts with visual explanations |
| 6 | Simulation | Allow mock trades and display performance metrics |

### *C. Experimental Setup*

The dataset comprises historical stock data (2020–2024) from Yahoo Finance and sentiment data from Twitter/Reddit. The hardware setup included an Intel i7 (12th Gen), 16GB RAM, and an NVIDIA RTX 3060 GPU. The system was trained with the following parameters:

- Batch size: 64
- Learning rate: 0.001
- Epochs: 100
- Optimizer: Adam

### *D. Quantitative Results*

TABLE IV
MODEL PERFORMANCE COMPARISON

| Model | Dataset | MAE | RMSE | Accuracy |
|---|---|---|---|---|
| ARIMA | NIFTY50 | 0.086 | 0.142 | 78.9% |
| LSTM | NIFTY50 | 0.052 | 0.087 | 91.2% |
| LSTM + Sentiment | Stock + Twitter | 0.041 | 0.072 | 93.8% |
| Edufin Hybrid | Stock + Reddit + Sentiment | 0.038 | 0.069 | **95.4%** |

The hybrid LSTM with sentiment fusion achieved a 17% improvement in forecasting accuracy over the ARIMA baseline, demonstrating the benefit of combining technical and textual indicators.

### *E. User Evaluation Metrics*

TABLE V
USER EXPERIENCE AND ENGAGEMENT EVALUATION

| Parameter | Metric | Score (out of 5) |
|---|---|---|
| Forecast Interpretability | Clarity of explanations | 4.7 |
| Educational Value | Relevance and understanding | 4.6 |
| User Engagement | Interaction frequency | 4.8 |
| Interface Usability | Ease of navigation | 4.9 |
| Overall Satisfaction | Average score | **4.75** |

The survey showed high satisfaction with interpretability, educational integration, and overall user experience.

### *F. Key Insights*

- Sentiment integration improved forecast reliability and responsiveness.
- Explainable AI enhanced user trust and comprehension.
- Gamified simulations increased learning motivation and retention.
- The architecture supports multi-asset scalability without redesign.

These results demonstrate that Edufin successfully bridges the gap between financial forecasting and education, enabling transparent and interactive financial learning.

## V. DISCUSSION

### *A. System Performance and User Insights*

The Edufin prototype was evaluated through simulated market scenarios using both historical and live data from Yahoo Finance and Twitter sentiment streams. The system produced promising results, with consistent forecasting accuracy across multiple financial instruments, including equity and crypto assets.

User testing revealed that participants found the platform intuitive and educationally engaging. The combination of visual explanations and simulation-based learning allowed users to better grasp complex trading concepts such as volatility, moving averages, and risk ratios. Many learners reported an improvement in their ability to interpret forecast results compared to traditional chart-based tools.

### B. Challenges Faced During Development

Despite the positive outcomes, several technical and operational challenges were encountered during the development and testing of Edufin:

**Data Quality and Noise:** Financial data from social platforms such as Twitter and Reddit often contained slang, sarcasm, or ambiguous sentiments. This made sentiment extraction a difficult task, as standard NLP models occasionally misclassified neutral or sarcastic remarks as positive or negative sentiments. Additional preprocessing and context filtering were necessary to improve accuracy.

**Model Overfitting and Generalization:** Initial versions of the LSTM-based forecasting model performed well on training data but failed to generalize effectively on unseen datasets. This issue was mitigated through regularization techniques, dropout layers, and the inclusion of diverse datasets from multiple market sectors.

**Explainability vs. Complexity:** While deep learning models offered high predictive accuracy, their black-box nature conflicted with the platform's educational goal. Balancing the trade-off between interpretability and model sophistication was one of the biggest challenges. The integration of explainable AI (XAI) methods like SHAP and attention visualization provided a partial solution but required additional computational overhead.

**Integration of Learning and Forecasting Modules** Merging the educational and analytical components presented both design and architectural challenges. Maintaining a smooth transition between forecast visualization and learning materials demanded an effective frontend-backend communication strategy and efficient data handling.

**Performance and Scalability Issues:** Handling real-time data streams and concurrent user simulations introduced latency and performance concerns. The team addressed this through caching mechanisms, asynchronous data calls, and containerization with Docker and AWS services.

### C. User Engagement and Gamification Effectiveness

The inclusion of gamification elements — such as badges, progress tracking, and leaderboards — significantly enhanced user motivation. Participants were more likely to revisit the platform, complete learning modules, and attempt new trading simulations when rewarded with points or recognition.

However, some users showed a tendency to prioritize leaderboard ranks over conceptual understanding, indicating that future designs must maintain a balance between competition and comprehension. Adaptive difficulty levels and concept-based rewards are planned for upcoming iterations to promote deeper learning outcomes.

## VI. Conclusion and Future Work

### A. Summary of Findings

The development of Edufin demonstrates the effectiveness of integrating artificial intelligence with financial education. By combining predictive analytics, sentiment analysis, and explainable AI techniques, the platform successfully delivers both real-time market insights and educational content that helps users understand the reasoning behind predictions.

Unlike existing forecasting systems that focus solely on accuracy, Edufin prioritizes interpretability, accessibility, and user engagement. Through modules such as the virtual trading simulator, backtesting engine, and gamified learning environment, users not only receive actionable market forecasts but also gain a deeper understanding of financial principles and decision-making processes.

Experimental results and prototype testing suggest that when users are provided with contextual explanations of predictions, their retention of financial concepts and confidence in trading decisions significantly improve. This confirms that a dual-purpose FinTech-EdTech platform can serve as an effective bridge between technical learning and practical application.

### B. Future Enhancements

Future research will focus on several key areas:

- **Personalized Learning Experience:**Integrate adaptive learning algorithms that customize course content and difficulty levels based on user performance, trading behavior, and learning style.
- **Advanced Predictive Models:**Incorporate Transformer-based architectures and reinforcement learning models to improve long-term financial forecasting and dynamic portfolio management.
- **Integration with Real Trading APIs:** Extend Edufin to connect with broker APIs (e.g., Zerodha, Binance, or Alpaca) to enable real-time paper trading and analysis of live transactions.
- **Multi-Language and Global Market Support:** Expand data pipelines to include global indices, commodities, and forex markets with multilingual sentiment analysis.
- **Explainable Large Language Models (LLMs):** Future iterations could integrate LLM-powered chat tutors (like FinBERT-LLM hybrids) to provide conversational explanations, strategy walkthroughs, and contextual advice.
- **Mobile Application Deployment:** Develop a cross-platform mobile version of Edufin using React Native or Flutter, allowing learners and traders to access predictions and learning modules on the go.

In summary, Edufin represents a forward-thinking innovation at the intersection of finance, artificial intelligence, and education. It transforms financial forecasting into an interactive learning experience, empowering users not only to trade intelligently but also to understand the logic behind each decision.

The platform paves the way for a new generation of intelligent financial education systems — where learning, prediction, and analytics coexist harmoniously. As AI and data-driven models continue to evolve, Edufin stands as a scalable foundation for personalized, explainable, and ethical financial learning ecosystems of the future.

## REFERENCES


[1] Victor Chang , Qianwen Ariel Xu , Anyamele Chidozie , Hai Wang - Predicting Economic Trends and Stock Market Prices with Deep Learning and Advanced Machine Learning Techniques - 2024

[2] Warda M. Shaba, Eman Ashraf, Ahmed Elsaid Slama - SMP-DL: a novel stock market prediction approach based on deep learning for effective trend forecasting - 2023

[3] GVS Swaroop, K. Manikanta, Dr. T. Bernatin M.E., Ph.D. - DESIGN AND IMPLEMENTATION OF STOCK PRICE PREDICTION USING DATA SCIENCE - Electronics And Communication Enginnering, Sathyabama Institute Of Science And Technology, Chennai, India. - 2023

[4] Wuzhida Bao a , Yuting Cao b , Yin Yang b , Hangjun Che c , Junjian Huang c , Shiping Wen a : Data-driven stock forecasting models based on neural networks - 2024

[5] Bledar Fazlija * and Pedro Harder : Using Financial News Sentiment for Stock PriceDirection Prediction - 2022

[6] Charalampos M. Liapis ,Aikaterini Karanikola ,Sotiris Kotsiantis : Investigating Deep Stock Market Forecasting with Sentiment Analysis - 2023

[7] Shubham Agrawal, Nitin Kumar, Geetanjali Rathee, Chaker Abdelaziz Kerrache, Carlos T. Calafate Muhammad Bilal : Improving stock market prediction accuracy using sentiment and technical analysis - 2024

[8] Jitendra Kumar Chauhan,Tanveer Ahmed ,Amit Sinha : A novel deep learning model for stock market prediction using a sentiment analysis system from authoritative financial website's data - 2024

[9] Mahmoud Darwish, Ehab E. Hassanien Amany H. B. Eissa : Stock Market Forecasting: From Traditional Predictive Models to Large Language Models - 2025

[10] Keane Ong, Wihan van der Heever, Ranjan Satapathy, Erik Cambria, Gianmarco Mengaldo : FinXABSA: Explainable Finance through Aspect-Based Sentiment Analysis - 2023

[11] Zijian Zhang, Rong Fu, Yangfan He, Xinze Shen, Yanlong Wang, Xiaojing Du, Haochen You, Jiazhao Shi, Simon Fong : FinSentLLM: Multi-LLM and Structured Semantic Signals for Enhanced Financial Sentiment Forecasting - 2025

[12] Sira Yongchareon : AI-Driven Intelligent Financial Forecasting: A Comparative Study of Advanced Deep Learning Models for Long-Term Stock Market Prediction - 2025