

**BASAVARAJESWARI GROUP OF INSTITUTIONS**  
**BALLARI INSTITUTE OF TECHNOLOGY &  
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(Recognized by Govt. of Karnataka, approved by AICTE, New Delhi & Affiliated to  
Visvesvaraya Technological University, Belagavi)

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**DEPARTMENT OF CSE-DATA SCIENCE**

**A Mini-Project Report On**

**“CALORIES BURNED PREDECTION”**

**A report submitted in partial fulfillment of the requirements for the**

**NEURAL NETWORK AND DEEP LEARNING**

**Submitted By**

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**Visvesvaraya Technological University**

**Belagavi, Karnataka 2025-2026**

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**DEPARTMENT OF CSE (DATA SCIENCE)**

**CERTIFICATE**

This is to certify that the Mini Project of SUPERVISED MACHINE LEARNING title  
“**CALORIES BURNED PREDECTION**” has been successfully presented by  
MOHAMMED MOINUDDIN 3BR22CD035 student of semester B.E for the partial  
fulfillment of the requirements for the award of Bachelor Degree in CSE(DS) of the  
BALLARI INSTITUTE OF TECHNOLOGY& MANAGEMENT, BALLARI during the  
academic year 2025-2026.

It is certified that all corrections and suggestions indicated for internal assessment have been  
incorporated in the report deposited in the library. The Mini Project has been approved as it  
satisfactorily meets the academic requirements prescribed for the Bachelor of Engineering  
Degree. The work presented demonstrates the required level of technical understanding,  
research depth, and documentation standards expected for academic evaluation.

Signature of Coordinators

**Mr. Azhar Baig**  
**Ms. Chaithra B M**

Signature of HOD

**Dr. Aradhana D**

## ABSTRACT

This project focuses on developing a calories burned prediction system using machine learning techniques to estimate energy expenditure based on physiological and activity-related data. Since calorie burn is highly dependent on sequential body movements and metabolic patterns, advanced deep learning models—particularly Long Short-Term Memory (LSTM) networks—are utilized to learn trends from historical activity records. The dataset undergoes preprocessing steps such as cleaning, normalization, and sequence generation to ensure that the model receives consistent and high-quality inputs. The system is designed to analyze patterns related to heart rate, step count, age, weight, duration of activity, and exercise intensity to generate accurate calorie burn predictions that can assist individuals, fitness trainers, and health-tracking applications.

To enhance real-world usability, the model can be integrated with live sensor data from wearable devices, enabling real-time calorie estimation. Furthermore, optimization techniques such as Elastic Weight Consolidation (EWC) are incorporated to maintain model stability and prevent catastrophic forgetting during continuous retraining with new user data. With reliable predictions and an efficient learning framework, this project highlights the potential of deep learning in personalized health monitoring and demonstrates how AI can support smarter, data-driven decisions for fitness planning and overall well-being.

# ACKNOWLEDGEMENT

The satisfaction that accompanies the successful completion of project work on “**CALORIES BURNED PREDECTION**” would be incomplete without the mention of people who made it possible, whose noble gesture, affection, guidance, encouragement, and support crowned our efforts with success. It is our privilege to express our gratitude and respect to all those who inspired us in the completion of this project work.

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## CHAPTER 1

# INTRODUCTION

Predicting stock market trends is a complex task due to the highly volatile and dynamic nature of financial markets. Traditional statistical models often struggle to capture the nonlinear patterns and long-term dependencies present in stock price movements. In recent years, deep learning techniques—especially Long Short-Term Memory (LSTM) networks—have gained significant attention for their ability to learn sequential data effectively. LSTM networks can analyze historical market behavior, identify hidden patterns, and generate accurate forecasts, making them highly suitable for time-series financial prediction. This project focuses on using LSTM to analyze historical NIFTY 50 index data and generate reliable predictions that assist traders in making informed decisions.

To further enhance performance, the system integrates Elastic Weight Consolidation (EWC), which helps maintain previously learned knowledge during retraining and prevents catastrophic forgetting. The project also incorporates real-time data collection using the Yahoo Finance API, enabling the model to generate live predictions based on the most recent market trends. By combining data preprocessing, deep learning architecture, model optimization, and real-time inference, this project demonstrates the practical application of neural networks in financial forecasting and highlights how AI can improve accuracy and decision-making in stock market analysis.

CHAPTER 2

OBJECTIVES

**Real-Time Stock Prediction**

The system aims to provide quick and accurate predictions for the NIFTY 50 index by analyzing historical stock data and generating real-time forecasted values using an LSTM model.

**Efficient Data Processing**

The project focuses on preprocessing, normalizing, and structuring financial time-series data to ensure the model receives clean and properly formatted inputs for improved accuracy.

**Model Accuracy and Performance**

The system is designed to minimize forecasting error using deep learning techniques and evaluate performance through metrics such as Mean Squared Error (MSE) to ensure reliability.

**Integration of Live Market Data**

The model fetches real-time NIFTY 50 values from Yahoo Finance, enabling the system to generate updated stock predictions based on the most recent market trends.

**Improved Model Stability (EWC)**

Elastic Weight Consolidation (EWC) is incorporated to prevent the model from forgetting previously learned information during retraining, ensuring long-term stability and consistency



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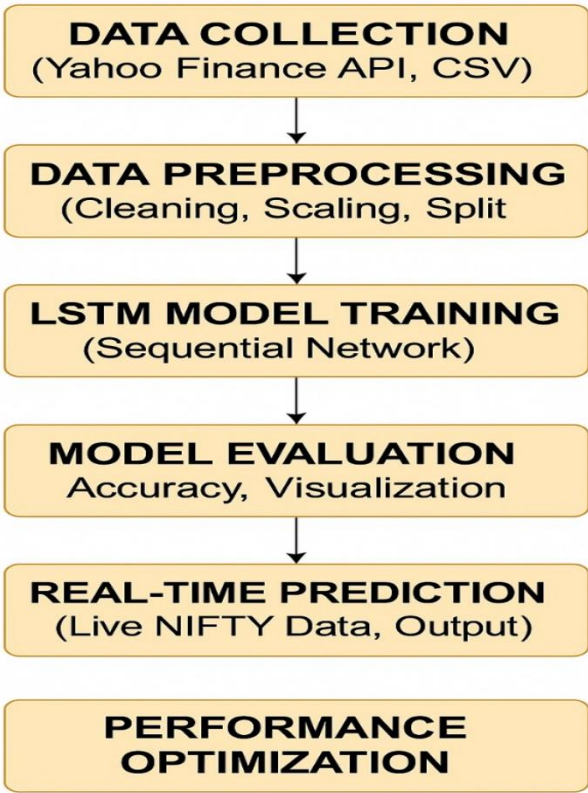
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## CHAPTER 3

### PROBLEM STATEMENT

To design and develop a deep learning-based LSTM model capable of analyzing historical NIFTY 50 stock data and predicting future price trends. The system should efficiently process time-series financial data to generate accurate real-time forecasts. It must also maintain stability during retraining by integrating Elastic Weight Consolidation (EWC).

METHODOLOGY



4.1 Block diagram

The system begins with Data Collection, where historical NIFTY 50 stock data is gathered using the Yahoo Finance API or CSV files. This data is then sent through Data Preprocessing, which includes cleaning missing values, scaling numerical features, and splitting the data for training and testing. The processed data is used for LSTM Model Training, where a sequential neural network learns time-dependent stock market patterns. After training, the model undergoes Model Evaluation to measure accuracy and visualize predicted vs. actual results. Once validated, the system performs Real-Time Prediction using live NIFTY data to generate up-to-date stock forecasts. Finally, Performance Optimization techniques like Elastic Weight Consolidation (EWC) are applied to enhance stability and improve long-term model performance.

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## CHAPTER 5

# REQUIREMENTS

### FUNCTIONAL REQUIREMENTS.

**Data****Collection:**

The system should collect historical NIFTY 50 stock data using the Yahoo Finance API or CSV files.

**Data****Preprocessing:**

It should clean, scale, and convert stock data into time-series sequences suitable for LSTM input.

**Model****Training:**

The system must train an LSTM model using the processed dataset to learn stock price patterns.

**Model****Evaluation:**

It should evaluate model performance using metrics like MSE and visualize predicted vs. actual values.

**Real-Time****Prediction:**

The system must fetch live NIFTY data and generate real-time next-day stock price predictions.

**Performance****Optimization:**

The model should implement Elastic Weight Consolidation (EWC) to maintain previous learning during retraining.

### NON-FUNCTIONAL REQUIREMENTS

**Performance:**

The system should generate predictions quickly with minimal delay, even during real-time forecasting.

**Accuracy:**

The LSTM model should maintain high prediction accuracy and low error under varying market conditions.

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**Reliability:**

The system must work consistently and handle live data without interruptions or failures.

**Scalability:**

It should be capable of handling larger datasets, longer time-series, and future model enhancements.

**Usability:**

The overall system should be simple, user-friendly, and easy to execute for both technical and non-technical users.

**Stability:**

The model should remain stable during retraining, with EWC preventing catastrophic forgetting.

**HARDWARE REQUIREMENTS**

**Processor:** Intel Core i5 / AMD Ryzen 5 or higher.

**RAM:** Minimum 8 GB (16 GB recommended).

**Storage:** At least 5 GB free space.

**GPU (Optional):** NVIDIA GPU for faster model training.

**Power Supply:** Stable power or laptop battery backup.

**Internet:** Required for fetching live NIFTY 50 data.

**SOFTWARE REQUIREMENTS**

**Operating System:** Windows 10/11, macOS, or Ubuntu.

**Programming Language:** Python 3.8 or above.

**Development Environment:** Jupyter Notebook, Google Colab, or VS Code.

**Libraries Required:** TensorFlow, Keras, NumPy, Pandas, Scikit-learn, Matplotlib, yfinance.

**Model Format:** Supports saving and loading models in **.h5** format.

**Version Control:** GitHub for storing and managing source code.

**CHAPTER 6**

**DESIGNS**

**Flow Chart**

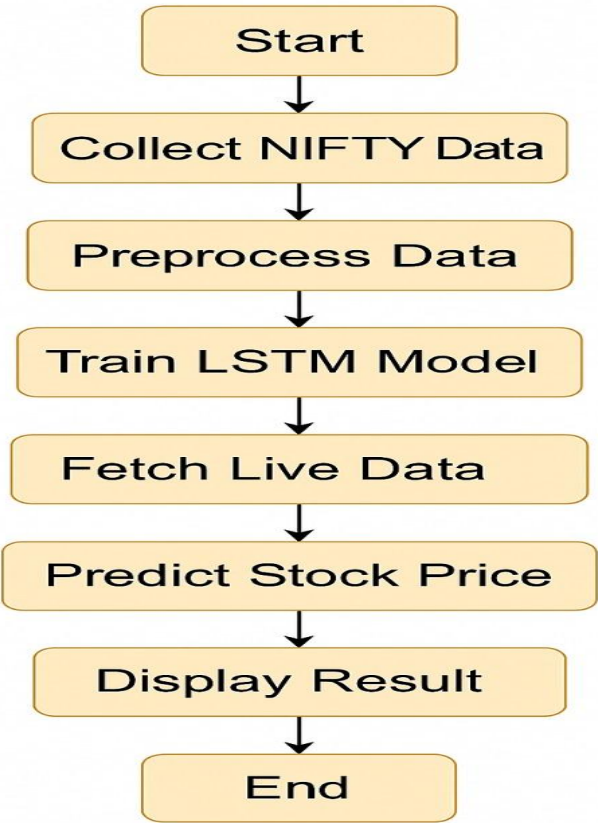
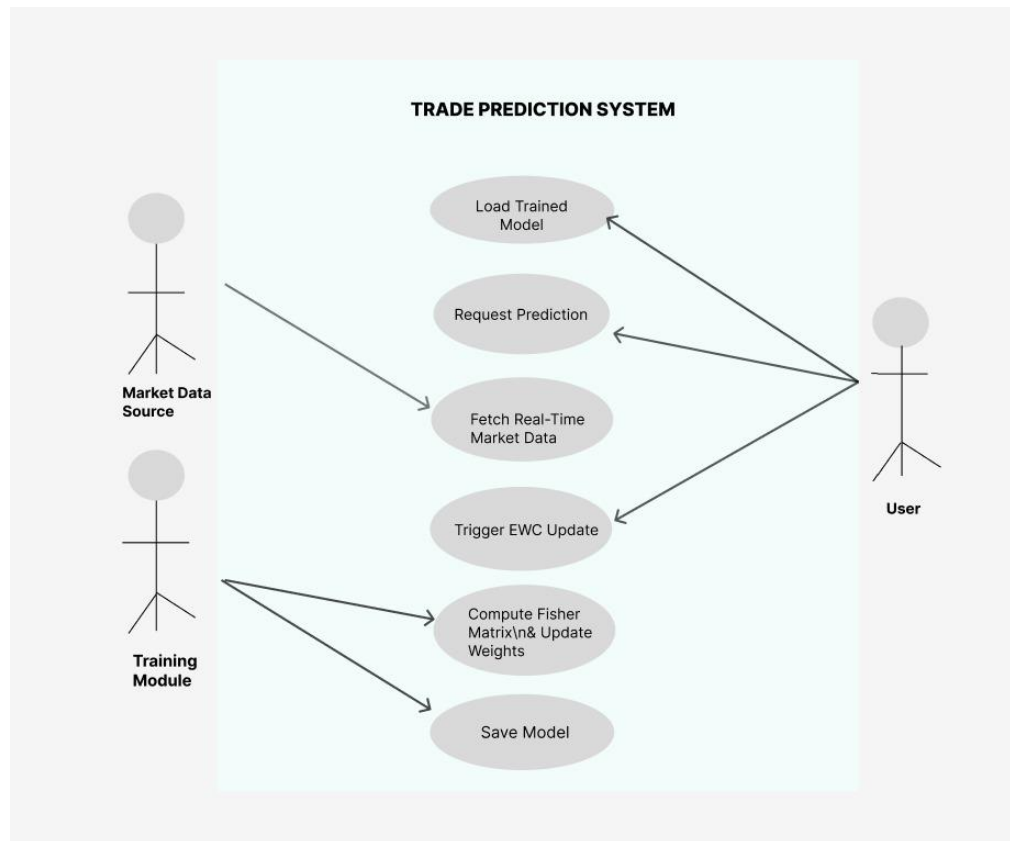


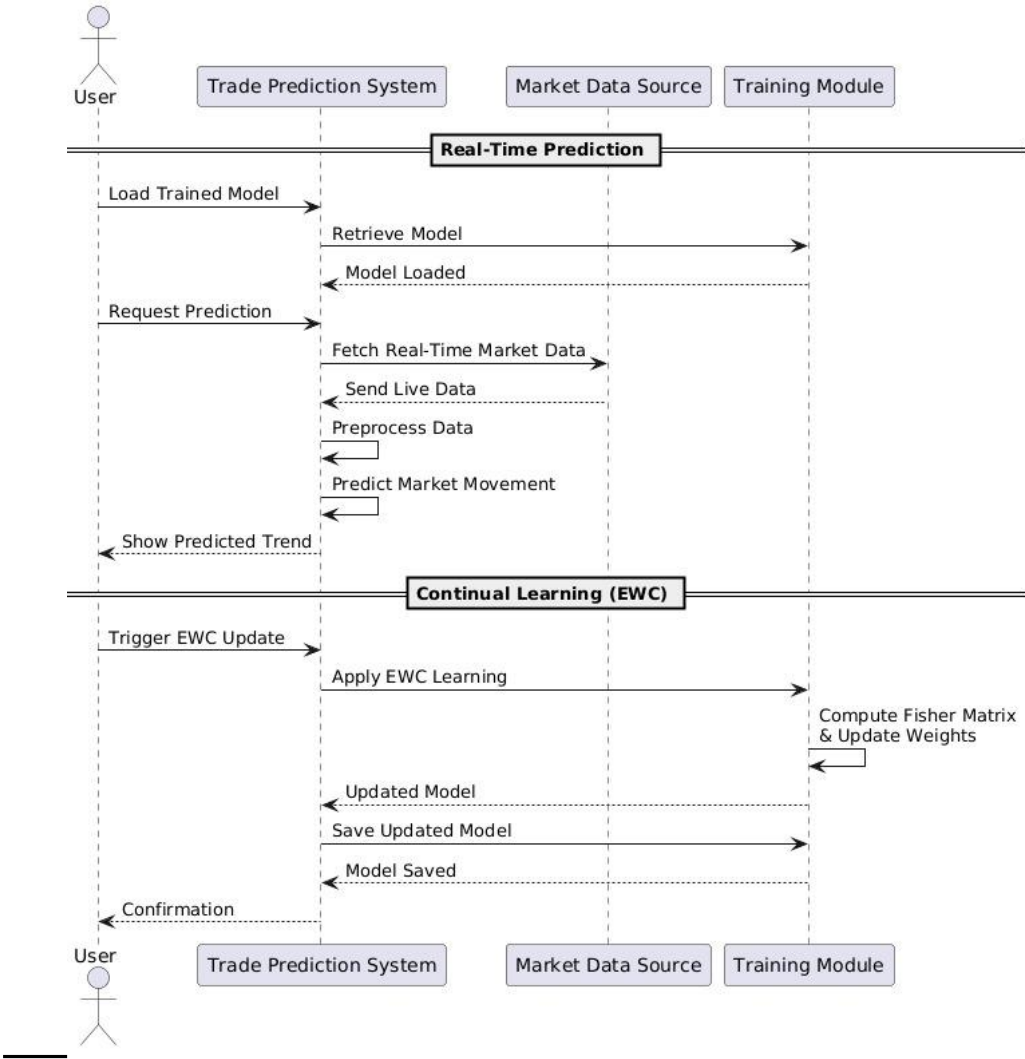
Fig 6.1 Flowchart

## Use Case Diagram



## 6.2 Use case Diagram

**Sequence Diagram**



**6.3 Sequence Diagram**



## CHAPTER 7

# IMPLEMENTATION

### Phase 1: Data Collection and Preprocessing

- Collected historical NIFTY 50 stock data using the Yahoo Finance API.
- Cleaned missing values, normalized numerical features, and converted the dataset into time-series sequences suitable for LSTM input.
- Split the data into training and testing sets for model development.

### Phase 2: Model Development

- Built an LSTM-based neural network using TensorFlow and Keras.
- Added LSTM, Dense, and Dropout layers to learn sequential market patterns.
- Compiled the model using the Adam optimizer and Mean Squared Error (MSE) loss function.

### Phase 3: Model Training and Evaluation

- Trained the LSTM model on the processed data over multiple epochs.
- Evaluated the model by comparing predicted and actual values using graphs and MSE.
- Saved the trained model in **.h5** format for future use.

### Phase 4: Real-Time Prediction

- Fetched live NIFTY 50 market data through the API.
- Loaded the saved model to generate real-time next-day stock price predictions.
- Displayed predictions and visualized market trends.

## **Phase 5: Performance Optimization**

- Applied Elastic Weight Consolidation (EWC) to improve model stability during retraining.
- Ensured the model does not forget previously learned patterns while updating with new data.

CHAPTER 8

RESULTS AND DISCUSSIONS

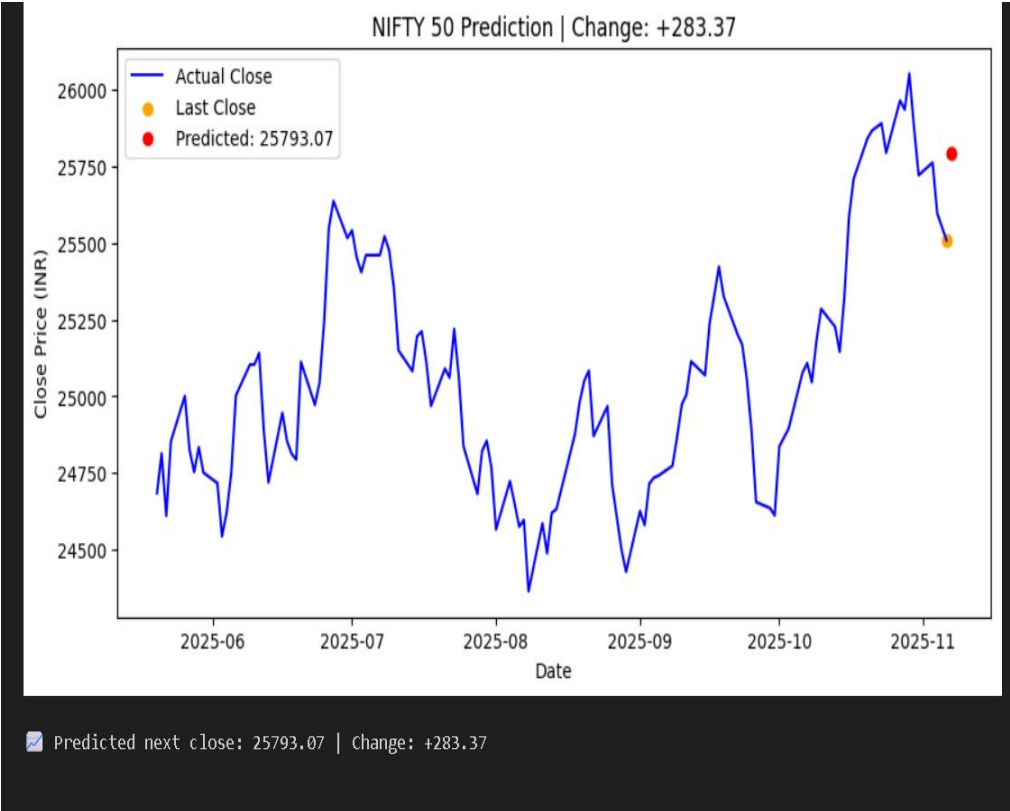


Fig 8.1 Output Graph

## **CHAPTER 9**

### **CONCLUSION**

The Real-Time Trade Prediction System using LSTM successfully demonstrates the use of deep learning for forecasting stock market trends. By learning from historical NIFTY 50 data, the model effectively captures time-dependent patterns and provides reliable predictions. The integration of real-time data enhances the system's practical value, enabling users to make timely and informed decisions. The addition of Elastic Weight Consolidation (EWC) further strengthens the model by improving stability during retraining. Overall, this project highlights the potential of AI-driven forecasting in financial analytics and showcases how neural networks can support smarter investment strategies.

## REFERENCES

- [1] M. Lee and J. Park, "Hand gesture-controlled document navigation using computer vision," in *Proc. IEEE*, 2021.
- [2] S. Verma and A. Gupta, "Voice-driven interfaces for accessibility enhancement," *Int. J. Comput. Appl. (IJCA)*, 2020.
- [3] K. Reddy and P. Singh, "AI-assisted document summarization and query systems," *Springer*, 2022.
- [4] OpenAI, "ChatGPT API reference," *OpenAI Documentation*, 2024.
- [5] Google Developers, "MediaPipe framework," *Google Developers Documentation*, 2023.
- [6] Alpha Cephei, "Vosk speech recognition toolkit," *Vosk Documentation*, 2024