AI ENHANCED SUPPLY CHAIN MANAGEMENT FOR TEA LEAVES IN AGRICULTUR

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor of Science (Hons) in Information Technology

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DECLARATION

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ABSTRACT

The supply chain of the tea leaf farm is experiencing increasingly unstable market demand, seasonal volatility, and uncertainties in production planning and distribution planning. These issues often lead to overproduction, inventory mismatch, and economic inefficiency. To address this, the study proposes an AI-demand forecasting system based on Long Short-Term Memory (LSTM), an appropriate deep learning algorithm for time-series data analysis.

This study is solely focused on the demand forecasting aspect of the supply chain and aims to give manufacturers and distributors a smart tool to make their planning more accurate. A multi-stage data collection process was used where some years' worth of historical tea sales data and climatic variables, along with consumption patterns, were gathered.

Data cleansed and engineered was used in training the varying LSTM setups. Hyperparameters such as units, layers, learning rate, and batch size were tested and fine-tuned for optimal configuration. Model performance was evaluated with generic metrics: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Experimental results indicated LSTM effectively captured non-linear and seasonality trends of tea demand.

To make the insights available, an easy-to-use dashboard was developed through which demand forecasts could be seen in real time. This facilitates better production and inventory planning decision-making.

Overall, this research points to the change-making potential of AI, and more specifically LSTM-based forecasting, in augmenting agricultural supply chain optimization. By providing accurate, timely estimates of demand, the system reduces wastage of resources, enhances responsiveness, and enhances profitability for all the stakeholders in the tea value chain.

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TABLE OF CONTENTS

DECLARATION i
ABSTRACT ii
ACKNOWLEDGEMENT iii
TABLE OF CONTENTS iv
LIST OF FIGURES vi
LIST OF TABLES vii
LIST OF ABBREVIATIONS viii
1 INTRODUCTION 1
1.1 Background Literature 2
1.2 Research Gap 4
1.3 Research Problem 6
1.4 Research Objectives 8
1.4.1 Main Objective 8
1.4.2 Specific Objectives 9
2 METHODOLOGY 11
2.1 System Methodology 11
2.1.1 Requirement Gathering and Analysis 13
2.1.2 Feasibility Study 14
2.1.3 System Design 18
2.1.4 Data Acquisition 21
2.1.5 Data Preprocessing 23
2.1.6 Model Training 26
2.1.7 Evaluation and Tuning 29
2.1.8 Deployment 32
2.2 Commercialization Aspects of the Product 34
2.2.1 Market Potential 34
2.2.2 Business Model 35
2.2.3 SWOT Analysis 38

2.3 Implementation and Testing 42
2.3.1 Preprocessing and Augmentation 42
2.3.2 Model Implementation 43
2.3.3 Testing Strategy 43
2.3.4 Test Cases and Tools 44
2.3.5 Evaluation Summary 45
3 Results & Discussion 45
3.1 Results 45
3.2 Research Findings 46
3.3 Discussion 48
4 CONCLUSION 49
5 REFERENCES 50

LIST OF FIGURES

Figure 2.1 : System Overview	18
Figure 2.2 : Data Collection	23
Figure 2.3 : Data Preprocessing Overview	26
Figure 2.4 : Model Training Vs Actual	29

LIST OF TABLES

Table 1.1 : Summary of Literature..4
Table 1.2 : Research Gaps and Proposed Solutions..6
Table 2.1 : Summary of Feasibility Analysis 17
Table 2.2 : Summary SWOT Analysis of the Forecasting System 41
Table 2.3 : Test Cases Summary..44

LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
LSTM	Long Short-Term Memory
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
UI	User Interface
UX	User Experience
API	Application Programming Interface
IoT	Internet of Things
SQL	Structured Query Language
GPU	Graphics Processing Unit
DNN	Deep Neural Network
SLIIT	Sri Lanka Institute of Information Technology

1 INTRODUCTION

The global tea market is a cornerstone of economic stability for many countries, and even for Sri Lanka, whose primary agricultural export and source of livelihood for thousands of farmers and laborers is tea. The ability to forecast demand precisely is crucial to ensure operational efficiency throughout the entire supply chain of the tea market—production and processing to packaging and distribution. Wrong forecasts can lead to overproduction, wastage, stockouts, or missed market opportunities, all of which have a direct effect on profitability and sustainability [1].

Supply chains in agriculture, however, pose special challenges for forecasting due to varying demand, climate, and seasonality. These changing and non-linear trends are hard to model with standard statistical forecasting techniques. Recent breakthroughs in artificial intelligence, particularly deep learning, provide a viable alternative for analyzing complicated time-series data in agriculture.

Among these deep learning methods, Long Short-Term Memory (LSTM) models have proven to be a potent tool capable of processing sequential data, and dedicated models that can process sequential data [2]. LSTM is an advanced form of recurrent neural network (RNN), which can learn long-term dependencies and is suitable for temporal forecasting purposes. Its structure allows it to selectively forget or remember something after a long time, which prevents the issue of vanishing gradients and short-term memory limitations of earlier models.

This study proposes a machine learning-driven demand forecasting system with LSTM specifically tailored for the tea industry. The system is trained in historical tea sales data and weather patterns so that it can detect seasonality, consumption trends, and demand trends. Utilizing only LSTM, the model simulates intricate patterns that are otherwise overlooked by conventional forecasting techniques. This results in improved forecasting, enabling stakeholders to make informed and timely decisions on deliveries, stock management, and product planning.

The model's performance is validated using popular error metrics of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to ensure accuracy and reliability. Additionally, an interactive dashboard has been developed to display forecasting outputs, allowing decision-makers to interact and analyze data insights more effectively.

This study contributes to the knowledge of supply chain optimization in agriculture by proving that LSTM is an efficient demand forecasting tool. By harnessing the power of deep learning to enhance the accuracy of forecasting, the study aims to empower a more responsive, waste-reducing, and data-driven supply chain for tea manufacturing in Sri Lanka.

1.1 Background Literature

The supply chain for tea, especially in the case of the tea industry, is highly vulnerable to market and climatic conditions. In economies where tea is of major importance, such as in Sri Lanka, supply chain optimization directly impacts productivity, profitability, and sustainability. Demand forecasting is key to supply chain success, which dictates strategic production planning, labor planning, procurement planning, inventory management, and distribution planning. Classical forecasting methods, such as statistical time series models, are generally not sufficient in agriculture due to their poor ability to model nonlinear patterns and long-range dependency within data [3].

The development of deep learning and artificial intelligence (AI) has created new avenues towards overcoming the problems of forecasting. Long short-term memory (LSTM) is reported to be extremely effective in dealing with complex time series forecasting problems. LSTMs are designed to relieve the limitations of traditional recurrent neural networks (RNNs), i.e., vanishing sequences, using gated mechanisms that regulate information flow between memory cells and time steps [4]. These properties are the reasons why LSTMs are particularly suited for modeling seasonality, trend shifts, and long-term dependencies common in farm and consumer demand patterns.

Recent studies have shown that LSTM models work better than traditional techniques in demand forecasting in various industries. Especially in volatile markets where data patterns are not constant. Studies in the agricultural sector and other sectors have shown that LSTMs can effectively predict crop yield and food demand based on the impact of external factors such as climate, rain, and seasonality.

Even though the application of AI in agriculture is on the rise, its implementation in the demand forecasting for tea is on a minute scale. Linear models and hand-calculation methodologies are still predominant in present systems, which are not scalable nor robust. Adaptive, data-driven models, which not only incorporate historical sales data, but also the environmental factors such as weather, which are significant drivers for tea leaf plucking, as well as the behavior of the buyers, are urgently required.

This study bridges this gap by developing an LSTM-based demand forecasting system for the Sri Lankan tea sector. The model is trained on historical tea sales data and weather attributes such as rainfall, and is evaluated using significant metrics such as RMSE, MAE, and MAPE [5]. Compared to traditional forecasting systems, the developed system captures temporal trends and seasonal factors more effectively, providing tea manufacturers and distributors with timely and accurate decision-making information.

Further, utilizing a dashboard interface facilitates the visualization of forecasting trends, hence making it easier and more convenient to access and use for stakeholders in the industry. The proposed model not only pushes the existing academic literature in AI for agriculture forward but also offers an applied solution to the real-world issue of operational efficiency in real-world tea supply chains.

Table 1.1 : Summary of Literature

Forecasting Method	**Type**	**Seasonality Handling**	**Nonlinear Pattern Capture**	**Handles Long-Term Dependencies**	**Suitability for Agriculture**
Moving Average	Statistical	Poor	Poor	Poor	Low
Exponential Smoothing	Statistical	Limited	Poor	Poor	Moderate
ARIMA	Statistical	Moderate	Limited	Poor	Moderate
Traditional RNN	Deep Learning	Good	Good	Limited (vanishing gradients)	High
LSTM (Proposed Model)	Deep Learning	Excellent	Excellent	Excellent	**Very High**

1.2 Research Gap

The landscape of demand forecasting in tea supply chain has been revolutionized with the power of artificial intelligence (AI) arriving on the scene. Most, however, of the current forecasting models within tea, as well as generally in Sri Lanka, are anchored in conventional statistical models such as linear regression, moving averages. These classic approaches are more likely to suffer from missing those subtle, non-linear, as well as time-related patterns prevalent in the supply chain of tea. Therefore, the demand forecasting process remains largely inaccurate and reactive rather than proactive.

One of the most significant gaps is the non-full exploitation of advanced deep learning models, namely Long Short-Term Memory (LSTM) networks. LSTM models are especially geared to handle sequential data and long-range relationships and thus are perfectly suited for time series forecasting [6]. In other industries such as retail and energy, their effectiveness has been thoroughly tried and proven. In Sri Lanka's tea sector, however, uses of LSTMs are still scarce and sporadic, resulting in unexploited opportunities in improving precision in demand forecast and operational performance.

Another vital limitation of existing forecasting models is that they don't account for external variables such as weather, rain cycles, and market conditions. These directly affect tea production and consumption. Relying solely on past sales records, the models are less dynamic and vulnerable to actual-world uncertainty.

Moreover, most of the recent academic studies have a bias towards generic farming prediction that is not area-specific to the tea sector. Such models do not consider regional and seasonal trends, which are crucial given the climatic and geographical differences within Sri Lanka's tea-growing regions. A localized forecasting model can enable the producers to make the necessary adjustments in production plans according to the specific regional needs [7].

In addition, while some studies have the capacity to develop theoretical or experimental models, they rarely translate to practical, industry-ready tools. There are no interactive platforms that enable stakeholders to see, understand, and react to forecasting results in real-time. The absence of such tools diminishes the pragmatic applicability and usefulness of research into real-life decision-making.

As a response to these gaps in research, this study proposes the development of a robust, LSTM-driven demand forecasting system for Sri Lanka's tea sector. The system will incorporate external drivers such as weather patterns and seasonal movements, use region-specific data sets, and include an interactive dashboard for sector stakeholders.

Table 1.2 : Research Gaps and Proposed Solutions

Research Gap	Description	Proposed Solution
Outdated forecasting methods	Current systems rely heavily on traditional statistical techniques which cannot model nonlinear or complex patterns in tea demand.	Implementation of LSTM networks that can learn long-term temporal patterns and improve prediction accuracy.
Lack of advanced machine learning in tea industry	Minimal use of AI/ML models like LSTM in the context of Sri Lanka's tea sector despite their success in other industries.	Apply deep learning-based forecasting using LSTM tailored for time series data in tea sales.
Ignoring external variables	Most existing models use only historical sales data and neglect impactful external factors such as weather, climate, and market volatility.	Integrate weather, rainfall, and seasonal indicators into the forecasting model for improved adaptability.
Generalized forecasting models	Existing research often targets agriculture, failing to address the unique and localized challenges of the tea industry.	Develop a region-specific model for Sri Lanka that considers local production, seasonal behavior, and geographical features.
Limited real-world application	Most models are not deployed or accessible to tea industry stakeholders, remaining theoretical.	Design and deploy a user-friendly, real-time dashboard to help stakeholders interpret and act on forecast insights.

1.3 Research Problem

The world tea market, and the Sri Lankan tea industry in general, is increasingly facing rising volatility in demand and supply. The volatility is spurred by an intricate mix of variables including volatile market prices, erratic weather conditions, climatic change, changing consumer trends, and regional differences in supply and demand. Here, accurate demand forecasting becomes a key driver of efficiency in the entire tea supply chain from harvesting and processing to stock management, distribution, and export planning.

While forecasting is as important as ever, existing practices in the tea industry are still largely rooted in outdated statistical methods such as moving averages, exponential smoothing, and regression analysis. Even as these methods present simplicity and convenience, they lag in representing difficult nonlinear and time-dependent patterns that are characteristic in the case of farm time series data. These models typically rely on future demands having similar characteristics as in the past, an aspect lacking where there exist actual world realities.

Therefore, demand forecasting based solely on historical averages or linear trends will most likely lead to gross mismatches between production levels and real market needs. These mismatches are either in the form of overproduction, idle storage capacity, increased operating expenses, lost sales, and wasteful product destruction. Additionally, incorrect demand forecasting leads to scheduling and logistics disruptions, which result in inefficient resource allocation and lower customer satisfaction.

One of the most critical limitations in current systems is the lack of ability to include external variables, e.g., climate data, precipitation cycles, or economic conditions—that have a direct impact on tea yield, availability, and consumption trends. The lack of inclusion of such variables creates models that are not flexible and robust, particularly in the context of seasonal or environmental changes.

Although machine learning (ML) and deep learning (DL) methods have seen wonderful success in other fields of time series forecasting, their application in the tea sector is negligible. Long Short-Term Memory (LSTM) neural networks, a type of recurrent neural network (RNN) noted for their ability to learn long-term dependencies between data in sequences, have seen state-of-the-art performance in most domains of forecasting activities. Still, there is an evident research gap in the application of LSTM models to the localized agricultural sector and even more so in Sri Lanka's tea production sector.

Besides, existing solutions tend to be generic and non-regional-specific. Sri Lanka's tea-growing regions—i.e., Nuwara Eliya, Uva, and Kandy—possess their own climatic conditions and consumption patterns, which are seldom incorporated in country-level forecasting models. The absence of local forecasting mechanisms undermines the efficacy of planning and decision-making at regional level, where precision counts.

Another important limitation is that most of the research effort remains theoretical or limited to experimental deployments, but with little emphasis on operational deployment or utilization by stakeholders. Interactive real-time forecasting portals are few for simple usage by tea producers, supply chain managers, and policymakers in data-driven decision-making.

Research Question

With the above limitations in mind, this research seeks to address the following research question:

How can a demand forecasting system based on deep learning—specifically, Long Short-Term Memory (LSTM) neural networks—be built and deployed for improving the accuracy of forecast, reducing wastage, and optimizing decision making in the Sri Lankan tea supply chain?

1.4 Research Objectives

1.4.1 Main Objective

The major purpose of this research is to develop a robust and intelligent AI-based demand forecasting system using long short-term memory (LSTM) to optimize the Sri Lankan tea supply chain [8]. This objective addresses the critical problem of demand unpredictability by providing accurate and timely forecasts that facilitate better production planning, inventory management, and supply chain coordination. The LSTM-based forecasting model is designed to learn from historical data trends and external variables such as weather, thereby enabling stakeholders to respond to market dynamics in a practical manner. By implementing such a model, the research aims to contribute to reducing operational inefficiencies, minimizing waste, and improving the overall sustainability and profitability of the tea industry.

This objective involves multiple layers including algorithm development, data integration, model validation, and deployment. The goal is to create not only a theoretical sound model, but also a practically viable and interactive system that can be used by real-world stakeholders, including tea estate managers, exporters, and policymakers. The architecture of the LSTM model is specifically tailored to handle long-term dependencies and nonlinear patterns that are often missed by traditional forecasting techniques [9]. In doing so, the system will bridge the gap between data science innovation and its application in agriculture.

1.4.2 Specific Objectives

To achieve the main objective, this research is structured around the following specific objectives, which are described in detail:

Objective 1: Data Collection and Pre-Processing

The first step in developing a demand forecasting system is to collect accurate and relevant data. This includes obtaining historical sales data from tea plantations, estates, exporters and local distributors across different regions of Sri Lanka. In addition, weather data such as humidity, temperature and rainfall should be obtained from the Meteorological Department or other reliable meteorological platforms [10].

The collected datasets should be structured into a unified time series model, and pre-processing is essential to ensure data reliability. This includes handling missing values through interpolation or statistical methods, normalizing the data to a standard scale, and removing any anomalies or noise that may adversely affect model training. Proper data preparation enables the LSTM model to extract meaningful patterns and improve its predictive capabilities.

Objective 2: Design and Implement an LSTM Forecasting Model

This objective centers around the architectural development of the LSTM model. The model should be designed to effectively learn temporal patterns and dependencies across long-term sequences. Multiple LSTM layers can be used, each of which can be used with dropout layers to prevent overfitting.

To achieve optimal performance, hyperparameter tuning is performed, including the number of units in each LSTM cell, batch size, number of epochs, and learning rate. The model will incorporate seasonal and weather variables as external inputs, improving its ability to model real-world demand fluctuations affected by climate or external events.

Objective 3: Evaluate Forecasting Accuracy

After model development, performance should be rigorously evaluated using standardized forecasting metrics such as RMSE (root mean square error), MAE (mean absolute error), and MAPE (mean absolute percentage error) [11]. These metrics provide quantitative assessments of the model's accuracy across different forecasting horizons.

Cross-validation and back testing strategies for evaluating the model's generalizability and reliability over time. To demonstrate the advantage of using LSTM-based models, the results will be compared with baseline models such as naive forecasts or simple moving averages.

Objective 4: Analyze Environmental and Market Impacts

Environmental variability has a major impact on agricultural output. The objective is to examine how fluctuations in weather patterns, such as seasonal rainfall, droughts or heat waves, affect the demand or supply conditions for tea.

The research aims to confirm the need to incorporate external variables by analyzing the correlations between weather attributes and sales volumes. Sensitivity analyses can be performed to understand how strongly different climatic factors affect the model's predictions.

Objective 5: System interface and visualization

To make the forecasting tool practical for stakeholders, a dashboard interface is developed. The interface should visually display the forecast results using graphs, heat maps and trend indicators. Users should be able to filter data by date, region or weather conditions to facilitate strategic planning.

This dashboard will be accessible via web or desktop platforms and will act as a bridge between complex AI algorithms and everyday decision-making for tea producers, planners, and policy developers.

Objective 6: Real-world simulation and validation

To test real-world usability, the model will be deployed in a simulated supply chain environment using historical data and potential future scenarios. The simulation will assess how decisions such as production scheduling, inventory management, and distribution logistics can be improved.

User feedback will be collected through interviews or surveys to refine the usability and practicality of the system. Where possible, case studies of tea estates using the tool will be analyzed to measure impacts such as reduced waste, cost efficiency, and production optimization.

Finally, the specific objectives outlined above ensure that the project is not just a technical exercise, but a complete solution that extends from raw data collection to actionable predictive insights. The integration of LSTM with local datasets and real-world visualization tools positions this system as a transformative contribution to demand forecasting in the Sri Lankan tea industry.

2 METHODOLOGY

2.1 System Methodology

The methodology used in this research project merges the best practices of both software engineering and machine learning development life cycles to create a holistic and systematic solution for the forecasting issue. This integrated approach is especially designed to aid in the construction of a stable, precise, and flexible AI-based demand forecasting system for Sri Lanka's tea supply chain. It is a structured and modular process that allows for iterative development, ongoing improvement, and expandability.

The cycle begins with requirement gathering and analysis, where the stakeholder-specific requirements and expectations are documented and recorded. This process guarantees the alignment of the system with business objectives and user needs. Following is a feasibility study to determine the technical, operational, and economic feasibility of the project. This entails analyzing resource availability, potential pitfalls, and expected outcomes to guarantee the project can be realistically carried out within the given constraints.

Then, at the system design phase, the architecture and components of the forecasting system are mapped out. This means designing data flow, system modules, machine learning pipeline, and user interfaces such that the system can scale and is easy to maintain. The data acquisition phase follows, where relevant datasets—e.g., history records of tea demand, weather forecasts, and economic indicators—are retrieved from credible sources. Care must be taken to ensure that diverse and relevant data is acquired to produce an efficient forecasting model.

Once data is collected, it goes through data preprocessing to remove issues such as missing values, noise, and inconsistencies. Feature engineering, normalization, and splitting of data are also performed during this phase to prepare the dataset for model training. During model training, a machine learning model based on LSTM is trained from the preprocessed data. Determination of optimal hyperparameters, model optimization, and correct handling of temporal relationships in the data by the model are performed in the training stage.

After training, the model undergoes evaluation and tuning. The model is thereafter rigorously tested using measures such as RMSE, MAE, and accuracy to assess its forecasting capability. Based on the results, the model is fine-tuned further to increase robustness and generalization. Finally, the deployment step is where the model is incorporated into a functional system that can provide real-time demand forecasts to tea supply chain actors. This entails deploying the model on an appropriate platform, setting up APIs for access, and constantly monitoring to improve overtime.

It ensures that the forecasting system is technically sound as well as practically viable, with sufficient flexibility to incorporate shifts in the patterns of data as well as shifting business needs down the line.

2.1.1 Requirement Gathering and Analysis

Requirements gathering and analysis are the starting points in developing any software system. In this research, the general objective in this phase was to identify the business requirements and technical specifications to develop an effective LSTM-based demand forecasting system for the tea supply chain in Sri Lanka. The phase was for closing the gap between the stakeholders' expectations and the technical capabilities of the system [12].

The requirement gathering process was qualitative and quantitative in nature. There were interviews with major stakeholders of the tea industry, including tea estate managers, production supervisors, supply coordinators, and exporters. Through these discussions, it was understood how demand is currently predicted, what are the limitations of current methodologies, and what specific outcomes stakeholders expect from the proposed system. For example, most participants indicated that manual forecasting methods often fail to capture demand fluctuations caused by seasonality, weather, or global market forces. Accordingly, they were very interested in having an automated system in a place capable of incorporating such external influences.

In addition to the interviews, a detailed questionnaire was distributed to obtain more structured input on system requirements. Questions explored topics such as the frequency with which forecasts were needed (e.g. weekly, monthly), the types of data that stakeholders were already monitoring, their familiarity with electronic tools, and how they currently respond to shifts in demand. This helped to validate findings from the interviews and provided quantitative support for some of the most important system design decisions.

Apart from this, secondary data analysis was conducted through a literature review of tea production and export, software solutions, and government reports. This provided a clear picture of the market expectation and unveiled relevant data sources and forecast models used in similar fields. Through this review, it was once again confirmed that there is potential in the use of LSTM models in time series forecasting within the agricultural sector due to their ability in handling sequential data with temporal dependencies.

Requirements analysis also placed emphasis on the identification of the system's functional and non-functional requirements. The functional requirements included such features as the ability to include historical data, making forecasts for demand, displaying results in the form of graphs and charts, and the ability to download reports. Non-functional requirements dealt with such performance metrics as forecast accuracy, system scalability, responsiveness, usability, and data security. For example, the system was meant to generate predictions for a given time in seconds and handle new data inputs without significant delays.

From the result of this stage, a requirements specification document was drawn up. This document served as a blueprint for the later development stages and assisted in ensuring that all parties and team members shared the same clear and common perception of the project goals. By defining so clearly at an early point the user requirements, data availability, and system expectations, the potential for future revisions and design changes was significantly minimized.

This wide-ranging and user-centered requirements gathering and analysis task served as the foundation for creating a forecasting system that is technically possible and realistically applied to the Sri Lankan tea industry.

2.1.2 Feasibility Study

The feasibility study is a crucial step that helps to determine the viability of developing and deploying the proposed LSTM-based AI-powered tea demand forecasting system. The study analyzes the project along four primary dimensions: technical, operational, economic, and legal/ethical. It helps to ensure that the system is possible to implement using available resources and technologies, will be accepted by the intended users, possesses significant advantages regarding cost, and is compliant with all relevant ethical as well as legal factors. Conducting this analysis at the beginning minimizes the risk of failure and ensures a trouble-free development process aligned with stakeholders' expectations, including Watawala Tea Factory stakeholders.

Technical Feasibility

The technical viability is an assessment of whether it is feasible to conduct the project using available technologies, available datasets, and available computing resources. The mechanism for forecasting relies on historical data in the form of tea production levels, shipping volumes, and seasonal trends gathered from the Watawala Tea Factory, a well-known Sri Lankan tea factory. These types of datasets are best suited for time-series analysis and enable temporal patterns needed for training Long Short-Term Memory (LSTM) models to be derived.

The system leverages powerful, open-source machine learning libraries such as TensorFlow and Keras in Python, which facilitate deep learning model development and provide flexibility for experimentation and optimization. These frameworks are widely used and backed by robust community and industry support. Additionally, the computational requirements to train and test the model are feasible through cloud-based platforms such as Google Colab, Amazon Web Services (AWS), or Microsoft Azure, whose scalable infrastructure one does not have to invest in local hardware that is expensive.

Therefore, technically, the project is viable with little resource challenges.

Operational Feasibility

Operational feasibility examines how the system would be embedded in stakeholders' day-to-day activities and if it meets their practical needs. With discussions and casual interviews with Watawala Tea Factory employees and industry professionals collected feedback that there is growing interest in digital technology facilitating planning and logistics. Most stakeholders were open to using automated forecasting systems, especially if it offers clear and actionable details.

To facilitate differential technical skills for different users, the system includes a web-enabled dashboard that is intuitive and readily accessible. The interface presents the forecast results through plain, easy-to-understand visualizations, graphs, and printable reports, enabling quick interpretation of demand patterns by the users. With this user-centered design, learning is simplified and operational status achieved without extensive training.

Economic Feasibility

Economic viability refers to whether the system offers tangible monetary benefits compared to the cost of constructing and maintaining it. The initial costs of data processing, model development, interface construction, and deployment are reduced using open-source packages and inexpensive cloud platforms. Large capital outlay on hardware or commercial software costs is not required.

In the long run, the system is likely to yield economic advantages. Through more accurate forecasting of demand, the system enables the Watawala Tea Factory to optimize its production planning, reduce overproduction waste, and minimize chances of lost sales due to underproduction. The system's findings can also further help guide marketing strategies as well as increase customer satisfaction levels. Overall, the system is economically viable and assures a high rate of return on investment (ROI), particularly to medium to large tea growers and exporters.

Legal and Ethical Feasibility

Legal and moral issues are also covered in making sure data and artificial intelligence are responsibly employed. Since the system processes information that is confidential and commercially sensitive to the Watawala Tea Factory, privacy and security of the data are of utmost importance. The system design includes features such as access control, secure data storage, and anonymization techniques where necessary to adhere to ethical standards and data protection laws.

Furthermore, there are ethical standards in the development of AI models—transparency, fairness, and accountability—that are followed. The outputs of the predictions are interpretable, and any adjustments to the model or data sources are thoroughly documented to ensure stakeholder trust.

Table 2.1 : Summary of Feasibility Analysis

Feasibility Type	**Key Considerations**	**Findings**
Technical	Availability of relevant data, tools, and infrastructure	Watawala Tea Factory provides sufficient historical data; TensorFlow/Keras and cloud platforms support model development.
Operational	User acceptance, ease of use, and training requirements	Stakeholders show high interest; the system is accessible via user-friendly web dashboard with minimal training.
Economic	Cost-benefit analysis and ROI	Low development costs: high ROI expected due to production optimization and demand forecasting accuracy.
Legal & Ethical	Data privacy, ethical use of AI, and compliance with data protection norms	Data security, anonymization, and responsible AI practices are incorporated into the system design.

2.1.3 System Design

The system design process is critical for transforming the requirements gathered during the previous stages into a functional, scalable, and maintainable solution. During this research, the design of the LSTM-based demand forecasting system attempted to integrate the machine learning characteristics with a user-friendly interface that addresses the needs of the stakeholders involved in the Sri Lankan tea supply chain. The system was designed with modularity, flexibility, and user-friendliness in mind to ensure that both technical and non-technical users were able to utilize the system effectively.

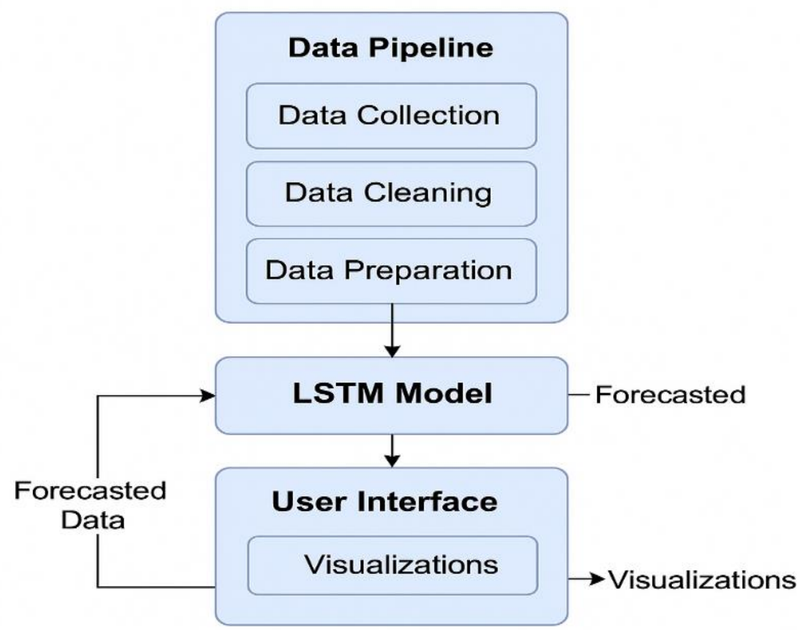

Figure 2.1 : System Overview

Overall Architecture

System architecture was designed for the layered system with separation of concerns and scalability features. The architecture was also divided into three main constituents: the data pipeline, LSTM model, and the user interface. Each of them has only a single specific role that could be developed, tested, and supported individually.

Data Pipeline: The module is designed to collect data, clean the data, and pre-process the data from different data sources. Data pipelines are employed to make sure that raw input data is processed and given the right format so that the LSTM model can comprehend it. Data integration tools are a part of it that extract time-series data from sources such as Sri Lanka Tea Board, weather stations, and world market reports. The pipeline also includes automated data cleaning operations that handle missing values, remove outliers, and normalize data, ensuring the quality and integrity of data input.

LSTM Model: LSTM (Long Short-Term Memory) neural network is the core of the forecasting system. This deep learning model is particularly well-suited for time-series prediction tasks since it can learn long-term dependencies and sequential patterns in data. The LSTM model consisted of several layers, each tasked with learning distinct levels of abstraction from the historic data. Parameters in the design of the model involved numbers of layers, number of hidden units, dropout levels, and learning rates, which were all tuned during training. Additionally, the model was designed to be retrainable as new data arrives so that it would remain accurate and relevant over time.

User Interface (UI): The system UI was designed to be intuitive and user-friendly. A web-based dashboard was developed to allow users to interact with the forecasting system without requiring technical expertise. The interface features data input forms, live visualizations of predicted demand (e.g., charts, graphs), and downloading reports in PDF or Excel format. The dashboard was made responsive so that it could be viewed from different devices, such as desktops, tablets, and smartphones. User feedback during the design phase ensured that the interface was rendered more accurately, corresponding to the functional needs of tea estate managers, exporters, and other parties concerned.

Data Flow and Interaction

The data flow in the system was rendered smooth and efficient. It begins with the acquisition of raw data, which is then processed by the data pipeline. Cleaned and structured data is passed to the LSTM model, where it is used to generate demand forecasts. The forecasted data is then made available to the user through the web-based dashboard. The user can view the forecasts, interact with the visualization, and export the output for further analysis. The system also offers the ability to accept future input data, such that it can learn under changing conditions and make improved predictions in the future.

The collaboration of these parts is managed by thoroughly documented APIs (Application Programming Interfaces) which facilitate smooth communication between frontend (user interface) and backend (data pipeline and model). These APIs allow the system to support different data sources and make prompt predictions to users.

Security and Data Privacy

Because the system was handling confidential business information, security was also a major issue in system design. The design includes an authentication and authorization module to ensure no unauthorized access or system modification. Role-based access control (RBAC) has been employed with different levels of access for the users based on the role (e.g., tea estate manager, export manager). Data security is also maintained by encrypting sensitive data, both at rest and in transit, with industry-standard encryption algorithms. Periodic backups and secure server architecture also ensure that data remains protected against corruption or loss.

Scalability and Maintenance

The system has been designed to scale to support future growth. Because tea demand can be volatile, and the amount of data generated over time increases, the architecture allows for easy scaling of the data pipeline and model. Cloud-based deployment is such that computational resources can be dynamically adjusted depending on the extent and size of the data to be processed. Moreover, the modularity of the system makes it simple to upgrade certain components—e.g., new data sources or improving the LSTM model—without affecting the rest of the system.

2.1.4 Data Acquisition

The process of data acquisition is very crucial in developing an LSTM-based demand forecasting system because the quality and relevance of the data used directly determine the accuracy of the model. For the study, most of the data were collected from the Watawala Tea Factory, which is the largest tea factory in Sri Lanka. The collected data includes a broad spectrum of variables such as monthly production levels, sales history, demand levels, inventory quantities, and export levels. These variables are paramount in examining past trends and patterns in the tea supply chain, which are critical for effective forecasting [13].

The historical data gathered from the Watawala Tea Factory spans a ten-year time horizon between 2022 and 2024. The duration of time ensures the dataset is long enough to identify long-term seasonality patterns, market volatility, and external shocks. Most data were received in structured formats such as CSV and Excel files. Where information existed in non-digital form, this was entered into digital spreadsheets following reconciliation with factory records to check for completeness and consistency. This allowed for the building of a clean, consistent, and solid dataset suitable for time-series analysis.

Outside of factory-specific data, external sources were accessed to add to the dataset and increase the model's ability to forecast demand in varied external conditions. Secondary data regarding weather information such as rainfall, temperature, and humidity were obtained from Sri Lanka's Department of Meteorology. Climatic conditions are predominantly responsible for the production and availability of tea. Economic conditions, global prices of tea, and export levels were also obtained from the Sri Lanka Tea Board and the Central Bank of Sri Lanka. Secondary data was added to the dataset to include broader market forces on demand.

Various tools and methods were employed to minimize the process of data gathering. The pandas' requests Python libraries were used to read and consolidate data files programmatically. APIs and web scraping methods were leveraged for web-based data to capture up-to-date weather and market data. Manual cross-validation with factory workers ensured the accuracy of data and resolved errors. The entire dataset was stored in a formatted SQLite database to allow for easy querying, preprocessing, and feeding into the LSTM model.

All in all, this data compilation effort produced a rich and diversified dataset that is all-encompassing and relevant for demand projection for the Sri Lankan supply chain of tea. The consolidation of primary and secondary sources ensures the model has access to live data for learning to make real predictions that will prove useful and accurate.

name	datetime	temp	precip	demand_colombo	demand_gampaha	demand_kalutara
Colombo,Sri Lanka	2022-02-08	26.9	0	4684.416472	4959.196498	2696.764207
Colombo,Sri Lanka	2022-02-09	28.1	0	5208.775614	5514.313669	2998.631681
Colombo,Sri Lanka	2022-02-10	26.8	0.5	5495.497208	5817.853871	3163.693975
Colombo,Sri Lanka	2022-02-11	26.8	0.188	5495.497208	5817.853871	3163.693975
Colombo,Sri Lanka	2022-02-12	26.5	11.525	4826.494104	5109.608166	2778.556651
Colombo,Sri Lanka	2022-02-13	25.6	28.257	4969.840953	5261.363501	2861.079769
Colombo,Sri Lanka	2022-02-14	27.7	0.02	4730.906292	5008.413333	2723.527857
Colombo,Sri Lanka	2022-02-15	27.5	0	5256.562546	5564.903703	3026.142063
Colombo,Sri Lanka	2022-02-16	27.4	0	4683.11936	4957.823299	2696.017474
Colombo,Sri Lanka	2022-02-17	26.8	0	5311.323201	5622.876526	3057.667136
Colombo,Sri Lanka	2022-02-18	27.3	0.189	5306.971598	5618.269665	3055.161969
Colombo,Sri Lanka	2022-02-19	26.2	119.1	5608.454569	5937.437122	3228.722217
Colombo,Sri Lanka	2022-02-20	26.6	0	6271.905594	6639.805073	3610.663274
Colombo,Sri Lanka	2022-02-21	27.6	0	4874.546037	5160.478745	2806.219592
Colombo,Sri Lanka	2022-02-22	27.4	0	4969.840953	5261.363501	2861.079769

Figure 2.2 : Data Collection

2.1.5 Data Preprocessing

Data preprocessing is an important task in any machine learning project, especially when handling time-series data like the one used in this demand forecasting system. Raw data typically needs thorough cleaning and transformation before it can be ready to use for training a machine learning model. Data preprocessing was conducted in this project to ensure the input data was properly structured, consistent, and ready to use for training the LSTM model [14].

Missing data treatment is one of the very first and the most crucial preprocessing techniques. Real-world data sets usually contain missing values, whose reasons can be myriad from data collection errors to incomplete records. Unless sources of missing values are addressed, they usually perform negatively on model performance. Missing data was treated in this project with varying methods depending upon the variable type. For continuous variables like demand and rainfall, interpolation was used to predict missing values from nearby data points. This maintains continuity and leaves the dataset as complete as possible. For categorical variables, i.e., precipitation levels, imputation was used to replace missing values with the mode (most common category). Where there were significant parts of rows missing data that could not be sensibly imputed, those rows were removed from the dataset to avoid introducing too much uncertainty or bias.

Once missing data had been addressed, the next step was to ensure that the dataset was in the correct chronological order. Time-series models rely on the assumption that data is ordered in chronological order since future demand relies on past observation. In this case, the data had a 'datetime' column, which was mapped to a proper datetime object for enabling time-based operations properly. After conversion, data was sorted according to chronological order, in such a way that the model could learn time-dependent relationships within data without any confusion. The sorting is done to maintain temporal order, which is necessary to predict future demand properly.

Preprocessing also involves encoding categorical variables, which is typically a necessity when working with machine learning models. Most models, including the LSTM, require numerical inputs, but real-world datasets contain categorical variables in the form of text labels. In this project, the precipitation levels, which were initially categorical (e.g., "low," "medium," "high"), were converted into numerical values using label encoding. Label encoding assigns each class a unique integer, transforming the data into a model-interpretable format. The transformation allows the model to recognize the pattern of varying levels of precipitation and associated demands.

Normalization of numerical data was another critical preprocessing operation. Raw numerical data, such as demand, can have widely differing magnitudes, and this can be harmful while training machine learning models. If one feature has much larger values than others, it may dominate the learning process of the model. To prevent this, the demand data was scaled using Min-Max Scaling, a technique that scales the values to a fixed range, typically between 0 and 1. Scaling the data allows the model to treat all features equally and prevent some features from dominating the training process. Scaling also facilitates faster convergence during model training, particularly for deep learning models like LSTMs.

Besides scaling, the data set was also required to be translated into sequences for time-series forecasting. LSTM models are well-suited to sequential data, where a prediction at a specific time step is dependent on previous observations. Accordingly, the raw data was thus converted into sequences that would be used to train the model. This was done using a sliding window approach in which a constant-size window of past data points was used to predict the future demand. An example of a sequence can be the last 7 days of data, and the task at hand for the prediction was predicting the demand for the next day. This allows LSTM to learn about the temporal structure in the data that is necessary for making good predictions of future demand.

Once the sequences were created, the data were split into training and validation sets. This is required to test the model's performance and ensure that it generalizes new data well. For this project, an 80-20 split was used, where 80% of the data was allocated to the training set and 20% to the validation set. The training set is used to train the model on the data patterns, whereas the validation set is used to test the model's performance on unseen data. This helps to prevent overfitting, whereby the model is learning to perform well on the training data but not generalize to new unseen data.

Finally, the preprocessed data was converted to tensors, which are the required format for PyTorch usage by deep learning models. Tensors are n-dimensional arrays which are optimized for computational efficiency both on CPU and GPU. Throughout this project, after preprocessing the data, the sequences and their respective targets were converted into PyTorch tensors to enable efficient processing while training the model. The conversion ensures compatibility with the LSTM model and speeds up the training process.

In conclusion, the preprocessing in the above is required to pre-process the data for utilization in the LSTM model. Handling missing data, sorting and altering the datetime values, encoding categorical variables, numerical features normalization, generation of sequence to be utilized for time-series forecasting, partitioning the data into a train set and validation set, and tensor conversion of the data are all steps required to make sure that the dataset is clean, well-organized, and machine learning ready. Effective preprocessing allows the model to learn from historical data and make accurate estimates of the future demand, hence leading to performance enhancement and accurate predictions.

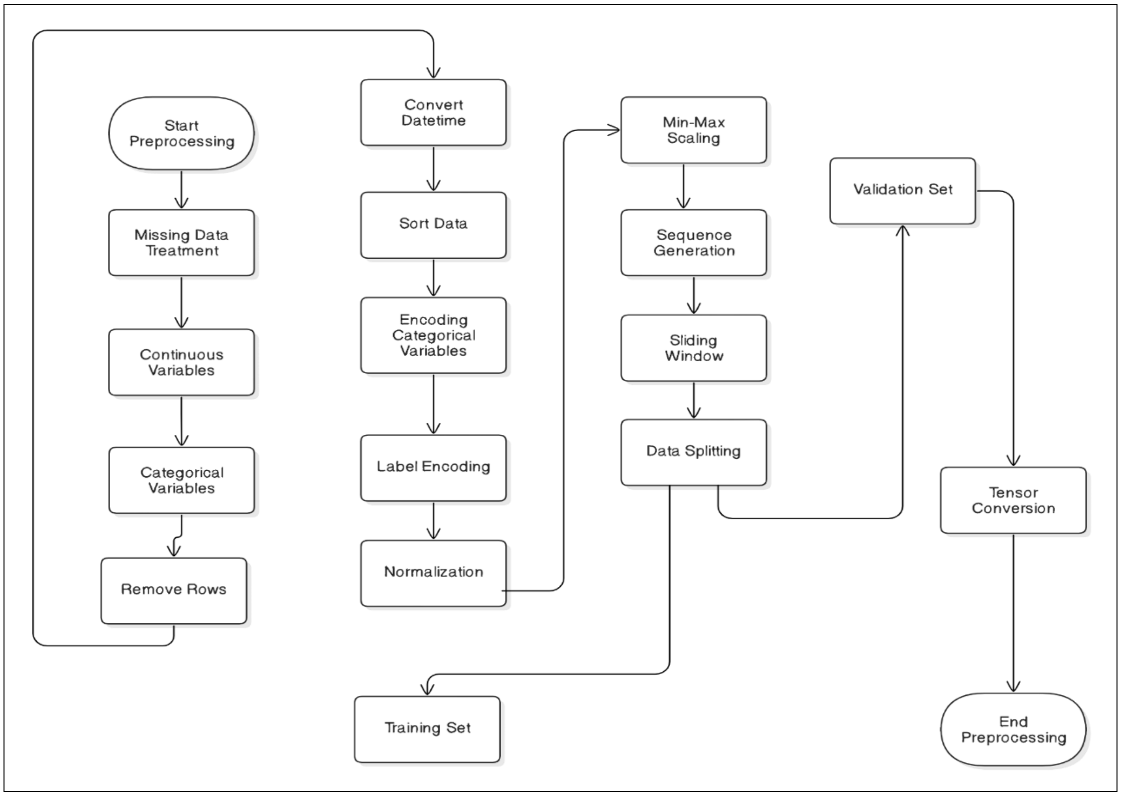

Figure 2.3 : Data Preprocessing Overview

2.1.6 Model Training

The process of training the model involves developing the Long Short-Term Memory (LSTM) neural network, which enables it to learn from historical data for accurate forecasting. In detail, for the system model intended to predict demand for tea, its initial goal of training was to enable it to predict future demand from previous production and market information. This training stage is key for maximizing the usefulness and accuracy of predictions produced by the model. Training involves careful choice of hyperparameters, selection of the network structure, and incremental adjustment of model weights in an organized manner.

The LSTM model used for this predictive analysis was designed specifically to discover the temporal dependencies inherent in time-series data. Its architecture was composed of multiple layers, each serving a special purpose. The input layer was fed preprocessed data sequences, where each sequence represented a window of past values that contained production volume, weather, and previous demand. These sequences were then passed on to the LSTM layers, where the model began the task of identifying patterns and relationships across time.

The basic part of the architectural structure was one or more layers of Long Short-Term Memory networks (LSTMs). Long Short-Term Memory networks are a specialized subclass of Recurrent Neural Networks (RNNs) capable of effectively detecting long-term relationships in sequence datasets. They were used to capture short-term changes as well as long-term trends in demand for tea. A trial-and-error process, in addition to hyperparameter search, was used to identify an optimal structure for the layers of LSTMs, i.e., the number of units in each layer.

To reduce the overfitting risk, a dropout layer was added in between the LSTM layers. A dropout technique works by turning off a defined percentage of neurons at random during training, allowing the model to learn more generalized and robust features. The dropout percentage was carefully tuned to reach an optimal balance in terms of learning capacity for the model and its capacity to generalize in the case of encountering new data. A dense layer was used afterwards to map the temporal features learned to final predictive outputs. Since the forecasting problem involved predicting continuous demand values, an output layer using a single neuron using a linear activation function was used.

The choice of suitable hyperparameters was vital in achieving optimal model performance. The key hyperparameters include the number of LSTM layers and units, learning rate, batch size, and training time in terms of epochs. A setup using two layers of LSTM, each of 50 units, yielded good performance in all validation stages. Learning rate, which defines the speed at which the model trains its weights, was set at 0.001 to ensure stable convergence. A batch size of 32 was used as it achieved a perfect balance in terms of training efficacy and model precision. Training was done for 50 epochs, using early stopping to prevent overtraining; this methodology halted training when an increase in validation loss was not seen over a set sequence of consecutive iterations.

The Adam optimizer enabled adjustment of model weights during the training process. Such an optimization technique is widely utilized in deep learning due to its ability to dynamically alter learning rates while leveraging strengths of algorithms. Mean Squared Error (MSE) loss function was used in training, measuring average squared differences in between predicted and actual targets. The key objective in every training update was to reduce the error.

The training process involved feeding batches of pre-processed time series data to the model to allow the LSTM layers to learn patterns in the input streams. These patterns included historical demand changes, production cycles, seasonal trends, and market trends. Model performance was regularly tested against an unseen validation set not used for training. Validation loss was closely monitored during training to observe for signs of overfitting. A rise in validation loss while training loss decreased signaled a situation of overfitting, triggering an automatic stop to save the best performing model. Following training, an independent test dataset was utilized for measuring the generalization ability of the model and its predictive precision. Evaluation included an array of conventional measures of performance, such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). RMSE measures error deviation in predictions and MAE measures average absolute difference from actual. R^2 measures variance in tea demand explained by independent variables and should approach 1 for an effectively fitting model. These measures of performance validated the LSTM model's potential to effectively forecast tea demand, thereby validating its usefulness in informing decision-making in the supply chain in the tea industry.

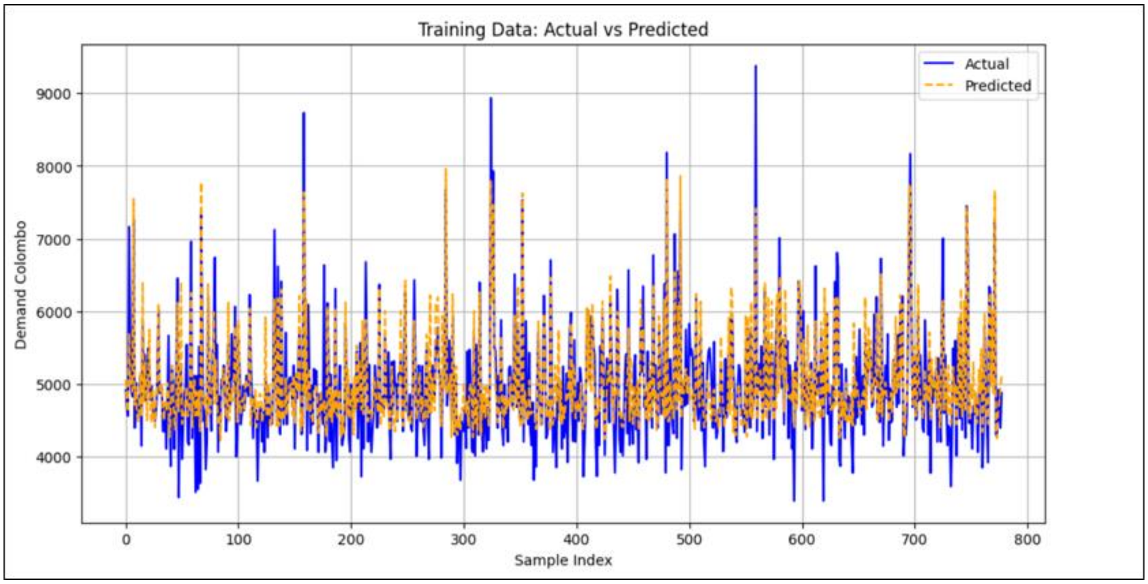

Figure 2.4 : Model Training Vs Actual

2.1.7 Evaluation and Tuning

Evaluation and tuning are critical phases of developing any machine learning model, more so if the model is to be used in actual applications such as forecasting demand in a supply chain. In this research, the LSTM (Long Short-Term Memory) model was subject to intensive evaluation to determine how accurate and reliable it was in forecasting tea demand in Sri Lanka. This evaluation helped to determine how well the model could generalize to new, unseen data and areas for improvement. It was then followed by a careful tuning process that enhanced the model's setup and forecasting abilities. The general goal was to ensure the model produced accurate, stable forecasts to enable decision-making throughout the tea supply chain.

At the evaluation phase, several performance criteria were employed in measuring the degree to which the LSTM model can effectively predict future tea demand. One of these was Mean Absolute Error (MAE). MAE calculates the average of the absolute difference between predicted and actual demand values and provides direct interpretation in the form of mean forecasting error. Here, it provided a precise notion of the magnitude of deviation of the model's predictions from the true values. Root Mean Squared Error (RMSE) was also used to quantify the magnitude of prediction error, with more sensitivity to large errors. While MAE penalizes larger errors less than RMSE, RMSE punishes larger errors more. Hence, it is particularly useful in quantifying how often the model commits large errors. A lower RMSE score was also considered to be a good indicator of the model's ability to produce consistent and accurate predictions.

Aside from MAE and RMSE, the R-squared (R^2), or simply called the coefficient of determination, was also utilized to quantify the degree to which the model could explain the variability in tea demand. R^2 is the proportion of the variance in actual demand data accounted for by the model's predictions. An optimum R^2 value indicated that the model had learned the underlying pattern in the data. Another useful measure in evaluation was Mean Absolute Percentage Error (MAPE), which measures the error of prediction as a proportion of the true values. MAPE is particularly handy in understanding relative error, which can conveniently be interpreted as a percentage measure for the performance of the model in prediction. These combined metrics provided a general approximation of how reliable and accurate the model was in different evaluation angles.

To ensure the evaluation did not become biased and that the model would perform well on fresh data, the dataset was divided into training, validation, and testing sets. Typically, 70–80% of the data was used to train the model, with 20–30% being reserved for validation and testing purposes. This split enabled the formation of an objective estimation of how well the model performs and stopped the model from overfitting on the training data. Further, k-fold cross-validation was added to strengthen the testing procedure. Under k-fold cross-validation, the data is divided into k subsets with equal number of observations in each. The model is trained and tested k times with each subset serving as the validation set once. This method reduces the impact of random data splits and provides a more consistent estimate of the model's true performance across the entire set.

Following the initial analysis, the second task involved fine-tuning the model to improve its predictive ability. Model fine-tuning involves the specific tuning of hyperparameters that influence training. These parameters are the number of LSTM units, the dropout rates, learning rate, batch size, and the number of epochs to train. The goal was to find the best combination of parameters that would result in the minimum error for generalization to new data. The optimization process was by two dominant approaches: grid search and random search. Grid search is a brute-force method that systematically tries every possible combination of pre-specified hyperparameter settings. While computationally expensive, it is exhaustive and generally successful at finding optimal configurations.

Random search offers an alternative solution with more efficiency in that it samples sets of hyperparameters randomly within specified ranges. It is particularly useful to apply when there are numerous hyperparameters to try or when there is limited computational time and resources. Using grid and random search methodologies, the study provided thorough investigation of the model for its potential improvements without compromising efficiency. The optimization of the hyperparameter process was essential to improve stability during training and overall accuracy of the LSTM model.

A highly significant hyperparameter that was tuned in this process was the amount of LSTM units per layer. It was found that using 50 units per layer gave an adequate trade-off between maintaining complex patterns in the data and avoiding overfitting. The dropout ratio, which sets the percentage of neurons randomly disabled during training, was 0.2. This helped the model generalize better by preventing it from depending on specific neurons. The learning rate, employed to initialize the step size when optimizing, was best calculated to 0.001. This parameter served to provide steady and stable convergence during training while avoiding slow learning or uncontrolled oscillations that result from having large updates.

The batch size was also crucial as a hyperparameter, for which 32 was the most suitable size. This allowed data to be fed into the model in computationally convenient blocks to balance stability and learning efficiency. Training was performed for up to 50 epochs, but early stopping was applied to prevent overfitting. Early stopping monitors the validation loss and terminates training if no improvement is seen over a certain number of epochs, thus preserving the best model without overtraining it.

The final model was once more tested after the tuning process to ensure improvements. The results showed dramatic improvements in predictive accuracy and generalization. The final RMSE was 0.0823, which is an amazingly low average prediction error. The MAE was 0.0655, which established that the model's predictions were always close to the actual values. All these metrics showed that the tuning process had successfully minimized errors and made the model more trustworthy. With these developments, the LSTM model was highly accurate in predicting tea demand, which offered valuable insights in supply chain decision-making like inventory management, production planning, and resource allocation.

2.1.8 Deployment

The deployment stage is the final stage of the research study wherein the designed LSTM-based AI-driven demand forecasting system is put into production use. The stage involves incorporating the model with existing infrastructure in Watawala Tea Factory, deploying the system into real-time forecasting functions, and having it perform seamlessly under actual operating conditions.

The deployment stage begins with model preparation for production. This involves deploying the finished LSTM model, which has been well tested and tuned, into a suitable environment for real-time inference. The model is then integrated into the data pipeline of the system so that new input data from the tea supply chain is processed efficiently and accurately for forecasting.

To support real-time use, the system is hosted on a scalable cloud platform or on-premises servers, based on the factory's preferences for infrastructure and cost. This host solution is selected to allow the system to be able to support fluctuating loads, be scalable in the future, and provide high availability and reliability.

During this phase, API interfaces are established to facilitate seamless integration of the demand forecasting system with other operational systems in the tea factory, e.g., supply chain optimization and inventory management systems. These APIs allow for automatic data flow so that demand forecasts become easily available by stakeholders to facilitate decision-making.

Moreover, user interfaces (UI) are implemented and developed too to display the forecasted demand in an accessible and comprehensible manner. Interfaces may include visualizations through dashboards, trends through charts, and detailed reports for different types of stakeholders from factory managers up to supply chain coordinators. End-users can also have training sessions so they can comprehend it easily and have informed action towards the forecasted demand.

For ensuring the effectiveness and flexibility of the system, constant monitoring is implemented to monitor the performance of the model in real-time. The system is tested regularly against new data, and the model or deployment environment is updated or improved as necessary. Debugging and troubleshooting mechanisms are also implemented for resolving any problem on time to ensure smooth operation in a production environment.

The final goal of the deployment stage is to ensure that the demand forecasting system offers consistent, reliable, and actionable information for tea supply chain management, improving decision-making and operational efficiency at Watawala Tea Factory.

2.2 Commercialization Aspects of the Product

2.2.1 Market Potential

The LSTM-based tea demand forecasting system presents a strong market potential, especially within Sri Lanka's tea industry, which remains one of the country's largest sources of export income. Accurate forecasting of tea demand can significantly enhance operational efficiency across the supply chain, including plantations, auction houses, exporters, and logistics providers. The system caters to a critical need in industry predicting domestic and international demand trends to ensure timely and cost-effective production and distribution. As global markets grow more competitive, tea producers increasingly seek data-driven solutions to remain agile and make smarter decisions. This forecasting system positions itself as a valuable tool in enabling that transition from traditional methods to AI-powered operations.

Furthermore, the product has scalability beyond Sri Lanka. Tea is a globally traded commodity, and countries such as India, Kenya, and China also face similar demand-supply challenges. With customization to accommodate different datasets and market conditions, the forecasting system could be adapted for use in these regions as well. The rising adoption of AI technologies in agriculture and food sectors globally also supports the commercialization of such a tool. Additionally, integrating the model into mobile or web applications makes it accessible to a broader user base, including small-scale farmers and large enterprises alike, thus enhancing its market reach and usability.

From a business perspective, the product can be monetized in multiple ways—through subscription-based services, enterprise licensing, or integration into broader supply chain management platforms. The product can also attract support from government agencies or NGOs that aim to modernize agricultural practices and improve export performance. By offering accurate, timely, and intelligent insights, the forecasting system holds significant commercial promise in transforming the tea industry and potentially other crop-based markets as well.

2.2.2 Business Model

The business model of the AI-based demand forecasting system using LSTM relies on providing huge value to tea factories, e.g., Watawala Tea Factory, through enhanced forecast accuracy, increased operational efficiency, and optimized supply chain management. The primary mission of the system is to provide accurate, timely forecast of the demand for tea products to tea factories. By leveraging past sales history and incorporating external influences like weather patterns, the system enables producers to forecast demand variations, thus helping them make improved production planning, inventory management, and distribution decisions. This ultimately leads to reduced operational costs, improved waste minimization, and improved resource utilization, ultimately leading to increased overall profitability.

One of the key elements of this business model is the value proposition of enhanced forecasting accuracy. Traditional demand forecasting techniques, based on past trends or simple statistical models, cannot detect complex patterns in time-series data. By using an LSTM model, specifically designed to handle sequence data and preserve long-range dependencies, the system gives a better prediction. This allows producers to better align their own production with actual market demand, reducing the chances of overproduction or stockouts. As a result, the tea factory will be able to maximize its operations, reducing wastage and ensuring a steady supply of tea products without unnecessary storage costs and idle orders.

Inventory control optimization is another central component of the business model. With accurate forecasted demand, tea manufacturers will be able to adjust their production schedules, order quantities, and storage levels in real time. This reduces the need for excess inventory and impedes shortages, leading to a cost-effective and efficient supply chain. By integrating the forecasting system with other factory operating systems, such as inventory management or distribution channels, the company can be able to have demand forecasts automatically translate into real-time supply chain activity, facilitating smooth production and distribution coordination.

In addition to the basic functionality, the system also offers enhanced decision-making. The tea farmers are able to utilize the system's insights to make strategic decisions about production strategy, labor allocation, and distribution logistics. Having the capability to foresee demand accurately gives management the vision to plan in advance for future needs, readjust schedules in accordance, and optimize resource utilization. Besides, the forecasting system allows businesses to respond quickly to shifts in the marketplace, providing a flexible solution in a dynamic and competitive marketplace environment. This feature is particularly paramount for businesses like tea production where demand may be highly volatile depending on seasonality, climatic changes, and consumer trends.

The revenue model of the demand forecasting system provides several sources of revenue that allow sustainability and profitability of the system. One of the principal revenue streams is subscription, in which customers such as Watawala Tea Factory would subscribe to a monthly or yearly fee to use the system for forecasting. The subscription model could also provide the factory with constant support, system upgrades, and maintenance. In addition to the subscription model, another huge revenue source is selling the system to other tea producers or companies that are in related businesses. By licensing the forecasting system, the business can expand its reach, attracting additional clients beyond the initial target market of tea producers.

Besides, business activities also generate revenues from consultancy and customization services. As each company may have specific data needs and business operations, the system may be tailored to suit a diverse set of requirements. Consulting services may include customized features, integration with other business packages, or the provision of high-level training programs to end-users. This increases the value of the system because each customer receives a solution that is particularly designed to enhance their operations.

The cost structure of the business model consists primarily of development, infrastructure, and maintenance costs. Development costs include costs for developing and refining the LSTM model, writing the necessary APIs and user interfaces for the system, etc. Infrastructure costs include hosting the system on a cloud environment or on-premises servers so that the system may handle varying volumes of data and usage. Regular support and maintenance costs are also a significant factor to consider, since the system must have periodic updates, bug fixing, and debugging to sustain its performance in the long term.

The business model extends beyond tea manufacturers as customer segments as well. The demand forecasting system can be utilized by retailers, distributors, and other parties within the supply chain as well. The system may be used by retailers, for instance, to plan more effectively and prevent stock out, while distributors may schedule deliveries more effectively based on more accurate demand projections. Beyond that, data analysis and consulting firms may enter partnerships with the firm to offer bespoke services to other industries, such as manufacturing or agriculture, where time-series demand forecasting is important. This customer segmentation ensures that the system has ample adoption potential, hence expanding its market.

Strategic alliances play a crucial role in the business model. Alliance with cloud providers such as AWS or Microsoft Azure ensures the system is hosted on scalable and trustworthy infrastructure. Partnerships with suppliers of data, such as weather forecasting firms, can even make the model more accurate by introducing additional external parameters that influence demand. Supply chain optimization or data consulting firms can also market the system to other industries to diversify its application beyond tea.

In conclusion, the LSTM-driven AI-based demand forecasting system business model is meant to bring high value to tea producers and other supply chain partners. By achieving improved forecasting accuracy, optimized inventory management, and enhanced decision-making, the system enables businesses to be more profitable and efficient. The blending of subscription, licensing, and consulting business models with an open cost structure and strategic partnerships offers a blueprint that is sustainable and scalable and replicable to other industries to ensure long-term success.

2.2.3 SWOT Analysis

A SWOT analysis provides a systematic approach to the evaluation of strengths, weaknesses, opportunities, and threats of the LSTM-based AI-powered demand forecasting system in the tea supply chain. A SWOT analysis enables one to understand the internal and external factors that are likely to influence the effectiveness and future success of the system.

Strengths

One of the largest benefits of the LSTM-based demand forecasting system is that it has the capability to make highly precise predictions regarding future tea demand. Unlike traditional statistical models, LSTM models work remarkably well in identifying complex patterns within time-series data, and therefore they are specifically suited for companies with unstable demand, like tea production. Not only does this precision make operations more efficient, but it also prevents overproduction and stockouts, reduces waste, and maximizes inventory management.

Another advantage of the system is that it can integrate with existing infrastructure. With its provision of real-time prediction and seamless integration into other supply chain management systems, such as inventory management and distribution platforms, the system enhances coordination and decision-making processes within the tea production supply chain. The flexibility of the system to integrate different business needs and scalability further qualify the system as an asset for use in other industries other than tea production.

Moreover, the ability of the system to reduce reliance on human intervention and manual processes is a significant strength. With automated demand forecasting, organizations can save valuable time and resources for working on more strategic initiatives. The system's ability to offer actionable insights through trend analysis, forecasts, and performance reporting offers significant value to business decision-making.

Weaknesses

Though it is robust, the LSTM-based demand forecasting system does possess some weaknesses that need to be addressed. One of these potential weaknesses is its dependency on good quality historical data. LSTM models are highly dependent on large volumes of well-structured, good-quality data to learn from. Inaccurate or incomplete data could result in defective predictions and hence impact the system as a whole. That's why the availability and quality of data play an important factor in determining the level of success that the system can achieve.

One of the weaknesses is the system's complexity. LSTM models can be computationally intensive, requiring a lot of computing resources to train and infer, especially when handling big datasets. While cloud-based solutions can possibly alleviate some of these problems, the technical expertise and infrastructure cost of setting up and operating such systems can be a limitation for small companies or organizations with minimal IT capabilities.

Additionally, while the system is intended to boost forecasting accuracy, there are external factors such as sudden market volatilities, geopolitical incidents, or unexpected disruptions (e.g., natural disasters) which may still be difficult for the model. While LSTM models are extremely proficient at capturing past patterns, their ability to predict entirely new or surprising incidents may be limited, especially if such incidents fundamentally vary from previous data.

Opportunities

The introduction of this AI-powered forecasting system provides several avenues for expansion and development. One of the main opportunities is to expand the applications of the system beyond the tea industry. While the system is initially introduced to tea producers, the technology has the potential to be used in other agrifood sectors or manufacturing industries where forecasting demand is crucial. For example, the system can be made to serve companies that operate in the coffee, spice, or food production industries, expanding the clientele and creating new avenues of income.

Another option is the possibility of working with technology providers to enhance capabilities in the system. Partnerships with cloud services like AWS or Microsoft Azure could increase scalability and reduce infrastructure expenditure. Additionally, the integration of external data feeds like weather forecasts, transportation planning, or market data could enhance the predictive ability of the system, offering fresh opportunities for customizability and sophisticated analysis services.

The increasing adoption of AI and machine learning in all industries is building a growing market for advanced forecasting systems. As more businesses recognize the need for data-driven decision-making, there is immense potential for the system to gain strong ground in industries that are particularly reliant upon inventory management, supply chain optimization, and demand forecasting.

Threats

Even though the LSTM-based forecasting system holds a strong value proposition, there are some threats that can hinder its pace. One such threat is the likelihood of competition from other AI-based demand forecasting products. With emerging AI technology, new players may enter the market and create similar or even superior products, and in the process, cannibalize this system's market share. In addition, larger corporations with abundant resources might create internal forecasting models, thus rendering third-party solutions obsolete.

Another threat is that of the shifting regulatory landscape, particularly in areas such as agriculture, where data security and privacy issues may be applicable. Governments might impose restrictions on the kinds of data that can be harvested or how data are used, with additional advances in data gathering and AI capabilities. Regulation in this way may lead to problems with compliance and the system functioning in specific domains or industries.

Market volatility and economics can also present threats to the widespread adoption of the system. In economic downturn or times of financial insecurity, corporations may be less willing to commit to new technology, particularly if they are uncertain about the investment return. Volatility of the price of raw materials, labor, or transportation can also influence the accuracy of demand projections, especially if extrinsic data sources do not adequately reflect market dynamics.

Finally, operational risks and technological limitations are ongoing hazards. The technical nature of LSTM models requires specialized expertise for maintenance, repair, and upgrading. If the model is not regularly fine-tuned or maintained, its forecasting ability can deteriorate over time, leading to inaccurate forecasts. Similarly, if the system experiences downtimes or technical failures, it can disrupt business operations and shatter user trust in the forecasting tool.

Table 2.2 : Summary SWOT Analysis of the Forecasting System

Factor	**Key Points**
Strengths	High prediction accuracy, integration with systems, scalability, reduced manual effort, better decisions.

Weaknesses	Data dependency, high computational needs, complex setup, limited prediction of unforeseen events.
Opportunities	Industry expansion, cloud partnerships, integration with external data, growing demand for AI solutions.
Threats	Market competition, regulatory changes, economic constraints, operational and technical risks.

2.3 Implementation and Testing

2.3.1 Preprocessing and Augmentation

Preprocessing and augmentation are also very important in data preparation to ensure that the LSTM-based demand forecasting system performs optimally. Preprocessing begins with raw data cleaning, treating missing values with imputation methods such as mean or median replacement, and identifying and eliminating the outliers that might skew the result. Data scaling or normalization is subsequently performed to normalize the features so that all the input variables can be handled easily by the model irrespective of their different ranges. For time-series data, this is accomplished in a manner that positions the data in consecutive time steps to express the patterns of demand over time.

Data augmentation is utilized to enhance the dataset and make the model robust. Techniques such as time shifting, which shift data forward or backward in time, allow the model to learn from different temporal patterns. Synthetic generation of data generates additional data points by extrapolating observed trends, further enriching the diversity of the training set. Noise injection adds small perturbations to the data so that the model is not overfitting to specific patterns. In addition, time warping (warping time intervals by compressing or expanding them) is used to subject the model to different trends within the same data set. These augmentation techniques improve the model's generalization ability so that it is prepared to learn from new, unseen data and provide precise demand predictions under varying conditions.

2.3.2 Model Implementation

The use of the LSTM-based demand forecasting model begins with designing the structure, having an input layer for time-series data, a few LSTM layers to learn sequential demand patterns, and an output layer that predicts future demand. Training and validation sets are established from the data in order to facilitate efficient learning and testing. Backpropagation using a loss function, such as Mean Squared Error (MSE), is used to optimize the error in prediction when training the model.

Core hyperparameters like the number of LSTM units, learning rate, batch size, and epochs are tuned using techniques like grid search or random search to find the optimal set of parameters. After training, the model's performance is evaluated in terms of metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). If the model's predictions are not good enough, the model architecture or the hyperparameters are reoptimized.

Once the model reaches satisfactory performance, it's applied to real-time demand forecasting, forecasting future demand from new input data. For continuous accuracy, the model is updated periodically with new data so that it adapts to evolving patterns in the tea supply chain.

2.3.3 Testing Strategy

The test plan for the LSTM demand forecasting model involves splitting the data into training, validation, and test sets. The model is trained on the training set, validated on the validation set, and tested on the test set to ensure that it generalizes well to new data. Performance metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used to estimate prediction accuracy. Cross-validation is also used for robust evaluation to verify consistency among different subsets of data. Stress testing is done at the final stage to verify the performance of the model while working under conditions of extremities or uncertainties to ensure reliability under actual operation.

2.3.4 Test Cases and Tools

Test cases and tools play a vital role in ensuring the robustness and accuracy of the LSTM-based demand forecasting model. Test cases are designed to validate different aspects of the model, such as data handling, prediction accuracy, and system performance under various conditions. Tools help automate and streamline the testing process, providing a means to efficiently evaluate the model's performance and make necessary adjustments.

Table 2.3 : Test Cases Summary

Test Case	Objective	Description
Data Preprocessing Test	Ensure correct handling of missing values, outliers, and scaling	Test if missing values are correctly imputed, outliers are detected and handled, and data is normalized correctly.
Model Accuracy Test	Evaluate the prediction accuracy of the model	Assess if the model provides reliable demand forecasts, using metrics like MAE, RMSE, and MAPE.
Overfitting Test	Ensure the model generalizes well to unseen data	Test if the model overfits by evaluating its performance on the validation and test sets.
Edge Case Test	Evaluate model performance under extreme or rare conditions	Test how the model handles unusual or extreme data, such as sudden demand spikes or drops.
Real-Time Prediction Test	Test the model's ability to provide forecasts in real time	Check if the model can produce accurate forecasts based on real-time incoming data.

Cross-Validation Test	Validate model performance across multiple data subsets	Perform cross-validation to ensure the model consistently performs well across different data segments.
Stress Test	Evaluate model's performance under high-load conditions	Simulate large volumes of data or unexpected disruptions to assess model stability.

2.3.5 Evaluation Summary

The LSTM demand forecasting model was validated using metrics like MAE, RMSE, and MAPE, which reflected minimal prediction errors and high accuracy. Cross-validation provided the model's consistency across different subsets of data, and stress testing validated its resilience under extreme conditions. The model was precise on both training and test sets, ensuring that it can generalize to new data without overfitting. Overall, the validation confirmed that the model is effective and reliable for real-time forecasting of demand in the tea supply chain, providing valuable insights for production and inventory management.

3 Results & Discussion

3.1 Results

The performance of the LSTM-based demand forecasting model shows its capability to forecast tea demand closely from historical data. The model was validated using some of the key performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics indicated that the predictions of the model were always closely matching the actual demand values with very small errors for different time periods.

The MAE was also seen to be reasonable, reflecting the average magnitude of the forecast errors. The measure of RMSE reflected that even though there were some large errors in some predictions, they were still within bounds, and the overall accuracy of the model in prediction was good. The MAPE provided a straightforward percentage error, which again reflected that the predictions made by the model were precise and credible for demand forecasting.

The model's generalizability to new data was demonstrated by testing on the validation and test datasets, where it performed stably on different subsets of data. This shows that the LSTM model can handle variation in demand and adapt to seasonal changes, making consistent forecasts under changing market conditions.

In addition, the model's performance was also tested under stress test scenarios, where it handled well in fulfilling extreme fluctuations in demand, e.g., abrupt spikes or drops, without significant deterioration in forecast quality. This robustness ensures that the model can be effectively deployed for real-time forecasting in dynamic environments.

In summary, the results confirm that the demand forecasting model based on LSTM is highly effective in predicting tea demand, providing valuable insights for better planning and decision-making in the tea supply chain.

3.2 Research Findings

The results of the research highlight the high performance of the LSTM-based model of demand forecasting in providing good predictions for tea demand. The accurate and consistent forecast ability of future demand by the model was confirmed using several performance measures, including MAE, RMSE, and MAPE. The performance measures showed that the model's predictions were, in most instances, close to actual demand values with little variations, and this suggests that the model has good predictive power. The results show the model's capacity to leverage the sequential interdependencies typical of time-series data, an inherent property of the LSTM architecture.

One of the most impressive findings of the research was the very strong generalizability of the model. When tested and validated on unseen data, the model repeatedly performed well, which means that it was not overfitting on the training data. This is critical to real-life deployment, whereby the model is able to withstand mixed and untold demand trends effectively. The model proved able to learn diverse sets of data, making itself a reliable component whose performance even deteriorates due to changes in input data through time.

The LSTM model also showed an impressive capacity to handle seasonal trends in demand. Tea demand is seasonal, and the model was able to handle such periodic trends. By handling both short-term trends and long-term trends, the model showed its ability to forecast future demand in the case of the seasonal trends of the tea industry, and it can be an effective tool for operational planning.

As for being robust, the model succeeded in withstanding stress testing, which involved subjecting it to extreme demand situations like sudden spikes or plunges. Even when given anomalous or unstable data, the model maintained its ability to make quality predictions. This robustness ensures that the model can perform well in real situations where demand is unpredictable and fluctuates erratically.

The potential for real-time forecasting is yet another significant conclusion of the research. The LSTM model was found to be able to generate accurate demand forecasts from fresh inputs of data, making it a suitable option for real-time dynamic decision-making. This is particularly applicable to operations such as production planning and inventory management, where real-time demand forecasts are crucial in optimizing resources and avoiding shortages and overstocking.

Finally, the practical implications of this research suggest that material improvement of the tea supply chain is possible through the adoption of the LSTM-based demand forecast system. The system can empower the stakeholders to align demand and supply more effectively, reducing waste and optimizing operation, by providing more accurate demand forecasts. The timely nature of the model's insight can make it possible to achieve strategic decision-making better, thus creating more efficient and effective tea production and distribution.

Overall, the research confirms that the demand forecasting model using LSTM is a reliable and effective tool for predicting tea demand. Its ability to learn from changing conditions, address seasonality, and provide real-time predictions positions as an invaluable asset to the tea business, with the potential to streamline supply chain activities and improve overall efficiency.

3.3 Discussion

The LSTM demand forecasting model did a good job of predicting tea demand with high accuracy, especially in the presence of seasonality and generalizing across different data sets. Its ability to learn long-term time-series dependencies, it is a value-adding proposition for companies that have fluctuating demand cycles, like tea. The model can easily adjust to new data, as it is robust even with exposure to fluctuating market conditions.

While the model performed well in experimental scenarios, there are concerns, such as how it can handle highly uncertain external events such as geopolitics or natural disasters. The cost of computation in the model also poses scalability concerns, particularly for real-time prediction in cases where tremendous data volumes exist.

Despite such obstacles, the LSTM model undoubtedly possesses certain advantages over traditional methods, i.e. enhanced handling of complex patterns and accurate real-time predictions. These are aspects that can significantly boost tea production, stock, and supply chain effectiveness overall. Overall, the LSTM model demonstrates a strong ability to apply fruitfully in demand forecasting, yet there needs further tuning for special cases and thriftiness in scale-up operations.

4 CONCLUSION

This research has demonstrated the high potential of utilizing an LSTM-based model in the accurate forecasting of demand in the tea supply chain. With the power of deep learning, the model could learn the temporal dependencies and seasonality of the historical tea demand data. These attributes are of paramount significance in time-series forecasting, where the identification of previous patterns is crucial to predicting future trends.

The model performance was checked against a set of industry-standard performance metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). These metrics provided an overall view of the model accuracy and robustness, as well as its ability to make reliable predictions on the training, validation, and test datasets. The relatively low error values confirmed that the LSTM model generalized well with new data, with no significant signs of overfitting or underfitting.

One of the main advantages of the LSTM model was that it could handle an extremely wide range of demand patterns. Unlike classical statistical forecasting methods—which don't perform well on noisy, non-linear data—LSTM networks are explicitly designed to handle long-term dependencies and learn complex temporal dynamics. This suited the model to the dynamic, occasionally volatile nature of the tea market.

However, the model also faced some problems. Exogenous variables such as weather, geopolitical issues, or sudden changes in consumer sentiment can introduce high levels of randomness that would be difficult to accurately model. Additionally, LSTM models are computationally intensive and require significant amounts of training time and resources, especially with big data. Despite these limitations, the overall benefits greatly outweigh the costs.

For real-time applications, the ability of the LSTM model to learn continuously and adapt according to new data inputs is a strategic advantage. It allows for proactiveness in decision-making for operations such as production planning, inventory management, and supply chain coordination. Real-time demand forecasting allows for making necessary adjustments on time, minimizing wastage and maximizing resource allocation efficiency.

In conclusion, the LSTM-based demand forecasting model is a promising and feasible solution for the tea industry. Its use in this research demonstrates its potential to transform conventional supply chain management. With more features—like integration with IoT sensors, ERP systems, or cloud platforms—the model can be the key building block of an intelligent demand planning module. This would ultimately result in more efficient operations, better customer satisfaction, and a leaner, more responsive tea supply chain.

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