AI ENHANCED SUPPLY CHAIN MANAGEMENT FOR TEA LEAVES IN AGRICULTURE

Research Group Final Report

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ABSTRACT

The tea industry has long served as a pillar of Sri Lanka's agricultural economy, contributing significantly to employment, rural development, and foreign exchange earnings. Among the key players in this sector, the Watawala Tea Factory stands out for its scale and strategic role in the national supply chain. However, despite its historical and economic importance, the industry faces mounting operational challenges. Volatile international market demand, seasonal production fluctuations, labor scarcity, logistical inefficiencies, and heightened environmental scrutiny are converging to place unprecedented pressure on tea manufacturers. This research responds to these challenges by developing and implementing an integrated, AI-powered framework that combines advanced demand forecasting with intelligent supply chain optimization.

Central to this study is the use of Long Short-Term Memory (LSTM) networks a class of recurrent neural networks known for their exceptional capacity to model time-dependent sequences and capture complex temporal patterns. The LSTM-based model is specifically designed to forecast short- and medium-term demand for tea products, enabling more precise production planning and resource allocation. The forecasting model addresses not only the cyclicality inherent in tea consumption but also the nonlinear impacts of external variables such as climate conditions, transportation dynamics, and workforce availability.

To ensure the model's predictive accuracy, a multi-stage, interdisciplinary data collection process was carried out. Historical sales data from the Watawala Tea Factory was aggregated alongside meteorological records (e.g., rainfall, temperature), transportation patterns (e.g., traffic congestion, route accessibility), and labor force metrics (e.g., worker availability, absenteeism rates). This diverse dataset underwent extensive preprocessing including data cleaning, normalization, feature selection, and temporal alignment to ensure consistency and analytical relevance. Multiple LSTM configurations were then trained, with careful tuning of hyperparameters such as the number of memory units, number of layers, learning rate, activation functions, and batch sizes. The performance of

each configuration was assessed using evaluation metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), all of which indicated the model's strong ability to capture underlying demand trends and seasonal variations.

Beyond demand forecasting, this research extends into the realm of green inventory management, integrating sustainability principles into the core of supply chain planning. Traditional inventory models often overlook environmental costs associated with overproduction, excessive storage, and unmet demand. In contrast, this study incorporates a green-oriented approach that translates monthly demand predictions into granular, weekly material and labor requirements. This enables the minimization of waste and resource inefficiencies while balancing service level objectives and environmental considerations. For example, predictive algorithms are applied to optimize raw material procurement schedules, reduce energy consumption in storage, and anticipate stock-out risks all while aligning operations with sustainability benchmarks.

In parallel, predictive analytics tools are leveraged to optimize logistics and labor deployment. Transportation models utilize real-time and historical traffic data to minimize delivery delays and enhance routing efficiency. Simultaneously, labor forecasting models anticipate shortages and surpluses in the workforce, allowing for more adaptive and resilient scheduling that mitigates production bottlenecks.

A major practical contribution of this research is the development of a real-time, interactive forecasting dashboard. This user-friendly interface presents stakeholders ranging from factory managers to supply chain analysts with dynamic visualizations of forecast data, inventory levels, labor projections, and logistics alerts. The dashboard facilitates rapid, data-driven decision-making and fosters cross-departmental coordination.

Overall, this research illustrates how integrating LSTM-based AI models with sustainable inventory practices and predictive operations planning can transform conventional tea manufacturing processes. By enhancing forecast precision, reducing waste, and increasing system adaptability, the proposed framework offers a replicable and scalable solution for modernizing agro-industrial supply chains not only in Sri Lanka but across other tea-producing regions facing similar operational and environmental pressures.

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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 industry remains a vital economic engine for many developing nations, with Sri Lanka standing prominently as one of the world's leading producers and exporters. The tea sector not only drives national revenue but also sustains the livelihoods of hundreds of thousands of individuals across the value chain—from smallholder farmers cultivating tea leaves in rural highlands to factory workers, logistics personnel, and export handlers. In this context, the Watawala Tea Factory represents a critical node in the country's tea production ecosystem, handling high-volume processing and distribution to meet both domestic and international market demands [1].

Despite its strategic importance, the tea supply chain in Sri Lanka faces enduring structural and operational challenges. Market demand is subject to global economic fluctuations, changing consumer preferences, and competitive pricing pressures. Simultaneously, the supply side is influenced by factors such as seasonal weather patterns, climate change, unpredictable yields, and growing labor shortages. These overlapping uncertainties often result in suboptimal outcomes—ranging from excessive inventory and waste during periods of overproduction to stockouts and missed sales opportunities when demand spikes unexpectedly. These inefficiencies not only diminish profitability but also pose serious risks to environmental sustainability and social equity in the agricultural workforce.

Traditional forecasting approaches, often based on linear models or heuristic rules, are ill-equipped to handle the complexity and dynamism of modern agricultural supply chains. They fail to capture non-linear relationships, long-term dependencies, and the influence of external variables like weather or labor market fluctuations. This is particularly problematic in the tea industry, where accurate demand forecasting and resource allocation must be synchronized with both climatic cycles and volatile consumer behavior.

To address these challenges, this research proposes a robust and adaptive forecasting and supply chain optimization framework powered by Artificial Intelligence (AI), specifically employing Long Short-Term Memory (LSTM) networks. LSTM, an advanced type of recurrent neural network (RNN), is designed to process sequential data while overcoming the limitations of traditional RNNs, such as vanishing gradients and short memory spans. Its architecture includes memory cells and gating mechanisms that allow it to retain and prioritize long-term historical information while selectively updating short-term patterns, making it ideally suited for modeling agricultural time-series data where future trends are closely tied to past events.

The core objective of this study is to develop and deploy an LSTM-based forecasting system tailored to the operational needs of the Watawala Tea Factory. The system is designed to accurately predict monthly tea demand based on historical sales trends, weather variables (temperature, rainfall, humidity), and production records. These monthly forecasts are further refined into weekly raw material and labor requirements, facilitating more agile inventory planning, minimizing spoilage, and aligning production schedules with real-time market needs [2].

To build this model, a diverse dataset was assembled through a rigorous data collection process involving historical sales data, weather reports, factory output logs, and labor attendance records. The data was subjected to meticulous preprocessing, including noise reduction, normalization, temporal alignment, and feature engineering to enhance model accuracy. Various LSTM configurations were trained and optimized through hyperparameter tuning, including the number of neurons, number of layers, learning rate, dropout rates, and batch sizes. Model performance was validated using industry-standard evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), all of which confirmed the LSTM model's superior predictive capabilities in capturing both seasonal and non-linear dynamics.

In addition to demand forecasting, the study recognizes the growing importance of workforce planning, especially given recent demographic shifts, rural-to-urban migration, and the increasingly unpredictable availability of skilled labor. Labor shortages can severely disrupt factory operations, especially during peak processing seasons. To address this issue, the research extends the LSTM framework to develop a labor availability prediction model, leveraging historical attendance data, seasonal labor migration patterns, and weather conditions to anticipate workforce gaps. This enables factory managers to proactively adjust shift schedules, hire temporary labor, or redistribute workloads to maintain operational continuity.

To ensure practical applicability, the system is integrated into a web-based, interactive forecasting dashboard that provides real-time visualizations, decision alerts, and customizable reporting features. This digital platform empowers supply chain managers, planners, and stakeholders to make timely, data-driven decisions, transforming traditional reactive planning into a proactive and predictive management approach.

Importantly, this research aligns with global sustainability objectives. By reducing inventory waste, optimizing raw material use, and improving labor management, the system contributes to multiple United Nations Sustainable Development Goals (SDGs), including responsible consumption and production (SDG 12), decent work and economic growth (SDG 8), and climate action (SDG 13). The proposed framework promotes not only economic efficiency but also environmental stewardship and social responsibility—cornerstones of a resilient and future-ready agricultural sector.

In summary, this study offers a novel, AI-driven approach to overcoming longstanding inefficiencies in Sri Lanka’s tea industry. By integrating LSTM-based demand forecasting, green inventory strategies, and labor prediction tools into a unified decision support system, the research lays the groundwork for a scalable, intelligent, and sustainable supply chain model. The Watawala Tea Factory serves as a compelling case study with strong potential for replication across other agricultural domains and developing economies worldwide.

1.1 Background Literature

The tea industry is an integral part of many agricultural economies, especially in South Asia, where it represents a significant portion of export income and employment. In Sri Lanka, tea is not only a leading export commodity but also deeply woven into the socio-economic fabric of the country. Given the perishable nature of tea leaves and the seasonality of production, the entire tea supply chain is highly sensitive to external variables such as climatic conditions, labor availability, and volatile market demand. This sensitivity underscores the critical need for effective supply chain optimization strategies to ensure stability in productivity, profitability, and long-term sustainability.

At the heart of supply chain efficiency lies demand forecasting, which drives several interconnected processes including production planning, labor allocation, procurement scheduling, inventory control, and distribution logistics. Inaccurate demand forecasting can result in mismatched supply-demand balances, underutilization of resources, excessive stockpiling, and significant financial losses. However, traditional demand forecasting methods—primarily based on statistical models—have shown limited success in the agricultural domain. Techniques such as moving averages, exponential smoothing, and ARIMA models tend to assume linearity and stationarity in the data, making them ill-suited for the nonlinear, seasonal, and multivariate nature of agricultural time series data, particularly in dynamic environments like tea production [4].

In recent years, Artificial Intelligence (AI) and deep learning have emerged as powerful tools to overcome the limitations of traditional forecasting methods. Among these, Long Short-Term Memory (LSTM) networks—a specialized architecture within the family of recurrent neural networks (RNNs)—have demonstrated substantial success in modeling complex and temporal data patterns. Unlike conventional RNNs, which suffer from the vanishing gradient problem when learning long-term dependencies, LSTMs use gating mechanisms (input, output, and forget gates) to control the flow of information across time steps, allowing them to retain and utilize relevant long-term context. This capability makes LSTM networks particularly adept at capturing intricate seasonal fluctuations, shifting trends, and irregular intervals commonly found in tea demand data.

Several academic studies have validated the efficacy of LSTM-based models in sectors with volatile and non-linear demand patterns. In agriculture, LSTM networks have been successfully applied to crop yield prediction, weather-based forecasting, disease detection, and food demand estimation, often outperforming classical statistical and shallow machine learning models. LSTM's ability to incorporate external variables such as rainfall, temperature, and calendar events, alongside historical demand data, allows for more holistic and robust forecasting models. These qualities are crucial in the tea industry, where weather plays a vital role in determining the quantity and quality of plucked leaves and, consequently, production capacity.

Despite these promising advancements, the application of AI, particularly deep learning, in the tea sector remains in its infancy. Most factories and plantation managers still rely on manual estimation or simple spreadsheet-based models for forecasting, which are neither scalable nor adaptive to real-time changes. Such approaches often fail to account for external drivers like weather anomalies, festival seasons, labor unrest, and shifts in global tea consumption trends. Therefore, there is an urgent need for adaptive, data-driven forecasting solutions that can dynamically adjust to changing patterns and deliver high accuracy [3].

This research seeks to bridge that gap by proposing a comprehensive LSTM-based demand forecasting model tailored specifically for the Sri Lankan tea industry. The model integrates historical tea sales data, weather parameters (such as rainfall and temperature), and labor availability data to predict both demand and raw material requirements. By using performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error

(MAE), and Mean Absolute Percentage Error (MAPE) for evaluation, the proposed system ensures that the predictions are both statistically robust and practically actionable.

Furthermore, this study contributes significant technological innovation by integrating the predictive model with a web-based dashboard interface. This dashboard allows decision-makers—such as factory managers, supply chain coordinators, and policymakers—to visualize demand forecasts, identify trends, and make informed decisions regarding production planning and resource allocation. The accessibility and interpretability of forecasting output through visual charts and automated reporting mechanisms reduce the barrier to technology adoption in the sector.

The novelty of this research lies not only in the technical design of the forecasting model but also in its practical applicability to a real-world case study—the Watawala Tea Factory in Sri Lanka. By providing a replicable and scalable framework, the study contributes to both academic literature and industry practice, enabling a smoother transition from traditional forecasting systems to intelligent, AI-powered forecasting infrastructure in agriculture.

Table 1-1 Summary of Literature on Forecasting Methodologies

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**

Tea cultivation is an important segment of the economic situation in the majority of rural countries, particularly in Sri Lanka, which remains one of the foremost contributors to employment generation and foreign exchange revenue. As a high-value crop, tea requires careful monitoring during its cultivation and primary processing stages mostly plucking, which is a labor-intensive process. However, throughout the last ten years, the tea sector has been confronted with a severe and growing shortage of labor. Rural-urban migration, demographic aging, limited monetary benefits, and insecurity of casual employment have significantly widened the disparity between demand for and supply of labor. The direct effects of this shortage are operation inefficiencies, missed harvesting windows, lost yields, and diminished quality all of which undermine the long-term viability and competitiveness of the tea business.

In this regard, the arrival of Artificial Intelligence (AI) offers an opportunity for a paradigm shift in addressing disruptions in the tea supply chain due to labor. This work examines the application of AI in the form of Long Short-Term Memory (LSTM) neural networks for developing an intelligent labor forecasting model for tea farming. LSTM models are suitable for handling time-series data as they can capture long-term relationships and temporal patterns. Using past labor statistics, climatic conditions, and market indicators, the model proposed here will provide precise forecasts regarding the availability of labor in different tea-growing regions. The core objective of this research is to create a region-aware, AI-driven decision-support system that not only provides predictions regarding the availability of labor but also indicates potential shortages or excesses of workforce in relation to expected demand. This predictive power is needed to optimize labor deployment, minimize under-harvesting, and ensure continuity to supply chain operations. The system is envisioned to be adaptive, scalable, and connected with real-time sources of data using a cloud-based infrastructure, so that it could be practical and deployable by field planners and managers.

Despite the arrival of digital transformation in agriculture under initiatives like Precision Agriculture and Industry 4.0, labor forecasting has been a comparatively less discussed subject. All such existing innovations have focused on yield forecasting, soil estimation, automated watering and pest monitoring. Labor availability, although equally crucial, has previously been estimated based on heuristic methods or fixed past records, which at times fall short of understanding changing environmental and socio-economic influences on the labor force. Furthermore, while machine learning methods such as SVMs and Decision Trees can be employed to address some agricultural forecasting challenges, they fall short in addressing complex temporal relationships, something LSTM networks are particularly well-qualified to do. The work presented here is the first in addressing the tea industry's unique labor patterns., short picking cycles, seasonality, skill-dependent tasks feature that necessitate more complex and localized forecasting models. In addition, it addresses a pertinent literature gap by incorporating external variables like rainfall, temperature, and market demand into the forecasting equation. Unlike most literature, which aggregates across crops or considers national trends, this research is regional in focus, considering that labor supply can vary dramatically between places due to local climatic, demographic, and economic circumstances. By the incorporation of AI-driven forecasting with locale-specific variables, this research contributes to theoretical insight as well as real supply chain enhancement in the tea industry. It is aligned with broader objectives of sustainable agriculture, digital transformation, and supply chain resilience particularly in developing economies where tea is an important socio-economic activity. Eventually, the system proposed enables tea estate managers and supply chain planners to make proactive, data-based decisions to deploy wiser workforce management and more uniform agriculture production despite labor uncertainties.

1.2 Research Gap

1.2.1 Demand forecasting

In the context of the Sri Lankan tea industry, accurate demand forecasting plays a vital role in ensuring operational efficiency, minimizing resource wastage, and optimizing labor allocation. However, a significant research gap exists in the application of advanced AI-driven forecasting systems tailored specifically to the needs of the local tea supply chain[4]. While traditional methods—such as moving averages, exponential smoothing, and ARIMA models—have been applied in some contexts, these techniques often fall short in capturing the nonlinear, seasonally influenced, and multivariate patterns observed in real-world tea production and demand data.

Moreover, most of the existing research in the field focuses on generalized agricultural forecasting models or macro-level supply chain optimization, without addressing the unique characteristics and constraints of the tea industry in Sri Lanka. These models typically fail to incorporate key variables such as weather fluctuations, market trends, factory-level production capacity, and labor availability—factors that are critical for accurate and reliable forecasting at the operational level.

Another major gap lies in the underutilization of advanced deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, which are well-suited for time series forecasting due to their ability to retain long-term dependencies and learn complex temporal patterns. While LSTM-based models have shown promise in sectors such as energy, finance, and retail, their application in agricultural forecasting—especially in tea production—remains limited, both globally and within Sri Lanka. Existing implementations in the local context rarely utilize real-time factory data and often lack model tuning strategies or integration of external factors, resulting in suboptimal performance.

Furthermore, there is a clear absence of practical, user-friendly tools that integrate AI-driven forecasting models with real-time visualization capabilities. Most research does not go beyond the theoretical development of models, leaving a disconnect between technical innovations and real-world usability for factory managers and supply chain planners. This gap highlights the need for a comprehensive forecasting system that not only delivers high predictive accuracy but also supports real-time decision-making through an intuitive user interface.

Therefore, this research aims to address these gaps by developing an LSTM-based demand forecasting system using historical data from the Watawala Tea Factory. The system incorporates key internal and external variables, applies advanced model tuning techniques, and includes an interactive visualization interface to support practical deployment. By bridging the divide between theoretical modeling and operational usability, this study seeks to contribute a scalable, intelligent solution to enhance forecasting accuracy and improve supply chain management within Sri Lanka's tea industry.

Table 1-2 Research Gaps and Proposed Solutions Demand forecasting

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.

1.2.2 Smart Inventory Management

Effective inventory management lies at the core of operational success in agricultural supply chains, particularly within the tea industry, where the highly perishable nature of raw materials demands precise timing and quantities of procurement. Despite advances in forecasting technologies, most current systems predominantly generate demand predictions on a monthly basis, which, while valuable for strategic planning, fall short of meeting the operational needs of tea processing factories. The inherent variability in intra-month demand, driven by factors such as climatic conditions, fluctuating labor availability, and transportation schedules, necessitates inventory decisions at a finer temporal scale ideally on a weekly basis. Unfortunately, there remains a substantial gap in methodologies and frameworks that effectively bridge this temporal resolution gap by disaggregating monthly forecasts into weekly raw material requirements that accurately reflect the dynamic realities of the tea supply chain.

Monthly demand forecasting models, even those leveraging sophisticated deep learning architectures such as LSTM networks, often aggregate data to a level that smooths over critical short-term fluctuations. Such aggregation masks weekly or daily demand spikes or drops that directly influence procurement schedules, labor planning, and processing throughput. In the context of tea production, these overlooked short-term variations can lead to either overstocking of fresh leaves resulting in spoilage and increased holding costs or stockouts that halt production lines, diminish output quality, and erode customer trust. The absence of a systematic and adaptive approach to breaking down monthly predictions into weekly actionable plans means that tea factories operate with suboptimal inventory levels, compromising both economic efficiency and product quality.

Another dimension of this challenge stems from the perishable and seasonal characteristics of tea leaves. Once harvested, leaves require immediate processing to preserve flavor and quality, leaving little room for inventory buffering. This unique perishability constraint calls for inventory models that do more than just translate demand figures into raw material quantities; they must integrate the temporal perishability window, ensuring that procurement aligns tightly with processing capacities on a weekly basis. Current inventory systems often neglect these constraints or apply generic models that are better suited for non-perishable goods, leading to misaligned supply and processing schedules. There is a clear research gap in developing inventory models that account for perishability alongside short-term demand fluctuations to optimize raw material flow in tea factories.

Furthermore, the supply chain of tea is highly susceptible to external uncertainties such as erratic weather patterns, labor market volatility, and logistical delays. These variables introduce a level of unpredictability that cannot be effectively managed through static monthly forecasts alone. The lack of dynamic inventory adjustment mechanisms that can react in near real-time to changing supply conditions significantly hampers the tea industry’s ability to maintain smooth operations. Integrating real-time data streams—such as weather updates, labor availability indicators, and transportation status—into the inventory management process, and subsequently reflecting these inputs in weekly raw material planning, remains an underexplored area within tea supply chain research.

In addition, sustainability considerations are increasingly shaping agricultural supply chain practices, including those in tea production. Smart inventory management plays a pivotal role in minimizing waste and promoting resource efficiency by optimizing order sizes and timing. However, sustainability initiatives are constrained by the coarse granularity of existing demand forecasts, which do not enable precision in inventory levels. This mismatch results in unnecessary waste of perishable goods and inefficient use of resources, undermining the environmental goals of the industry. Consequently, there is an urgent need to develop inventory systems that not only respond to operational dynamics but also align with sustainable supply chain practices through enhanced temporal resolution and adaptability.

Lastly, despite the recognized benefits of AI and machine learning in forecasting demand, the literature reveals a scarcity of research that extends beyond forecasting into the operational translation of these forecasts into inventory control policies tailored for the tea industry. Most empirical studies focus heavily on improving forecast accuracy at aggregated levels, with insufficient attention given to how these forecasts can be operationalized in day-to-day inventory decisions. This research gap includes the lack of models that consider the unique characteristics of tea supply chains—such as perishability, labor seasonality, and climatic impacts—within the inventory planning framework. Without such integration, tea factories cannot fully leverage predictive analytics to enhance their inventory management practices.

In conclusion, while advanced forecasting models like LSTM provide robust monthly demand predictions, the critical research gap lies in developing a smart inventory management framework that effectively converts these monthly forecasts into granular weekly raw material requirements. Such a framework must incorporate perishability constraints, real-time supply chain variables, and sustainability principles to enhance operational efficiency, reduce waste, and improve responsiveness. Addressing this gap will empower tea factories, like the Watawala Tea Factory, to transition from reactive, heuristic-based inventory practices toward proactive, data-driven supply chain management, thereby supporting both economic and environmental objectives in the tea sector.

1.2.4 Labour Shortage

While the world has been increasingly interested in digitalization and intelligent agriculture, labor shortage in the tea industry—especially in a predictive and data-driven manner—is largely under-researched to date. While most of what has been researched in agricultural technology has been focusing on crop health monitoring, irrigation automation, and yield prediction, labor prediction, most notably in labor-intensive crops like tea, has received very little attention.

Contemporary forecast methods largely rely on fixed historical data or worldwide trend studies. These are not equipped to quantify the dynamic, high-order variables influencing labor availability such as local people movement, seasonal migration, rogue weather patterns, and demand volatility in the markets. As such, existing models are not responsive and situation-specific enough for effective labor planning in tea farming, where timing, skill, and climate sensitivity are highly critical.

Also, while classical machine learning algorithms like Decision Trees and Random Forests have been employed in some agricultural forecasting, they cannot model temporal dependencies, which is an important parameter in analyzing trends in labor availability over time. The newer deep learning techniques, namely the Long Short-Term Memory (LSTM) networks, have been very promising in time-series forecasting in general in various domains. Their application in labor forecasting in the tea industry, however, remains unexplored.

Even the limited literature that employs LSTM or similar models is too general, not including region-level variables or crop-level dynamics. Tea cultivation is highly localized, with large heterogeneity in picking cycles, climatic patterns, and workforce demographics at the regional and estate levels. This necessitates a tailored forecasting model that standard models are not able to provide. In addition, powerful external drivers such as rain, temperature changes, and spikes in market demand are frequently not considered within current labor forecasting systems, which makes them less field-worthy and credible.

Furthermore, while mechanized solutions to labor functions like tea plucking using AI have been proposed, they are quite capital-intensive and therefore not possible for smallholder farmers. These solutions are more focused on automation and less so on predictive workforce planning, thereby leaving a glaring shortfall in human resource optimization.

Finally, although existing studies on supply chain resilience in tea highlight stakeholders' cooperation and information sharing, they generally overlook the role of predictive labor analytics as an essential aspect of supply chain management.

Hence, there is a direct research gap in the development of AI-powered, region-based, and time-aware labor forecasting models for the tea industry. Addressing this gap through the application of LSTM networks and data-source fusion across multi-dimensional sources—such as weather patterns, market dynamics, and historical labor data—will significantly enhance labor planning, operational resilience, and supply chain efficiency in general. The present research endeavors to rectify this underappreciated yet imperative dimension of smart agriculture and provide an affordable, scalable solution to sustainable labor management in tea cultivation.

1.2.1 Logistics Management

In recent years, significant attention has been directed toward enhancing supply chain efficiency in the agricultural sector through the use of predictive analytics. Prior studies have shown promising results in areas such as crop yield forecasting, demand prediction, and logistics optimization across various products like rice, wheat, and dairy. However, when it comes to the tea industry—especially in countries like Sri Lanka, where tea plays a major economic role—the adoption of advanced predictive techniques remains limited. Most existing research related to the tea supply chain focuses more on qualitative elements like labor management, production processes, or cost-saving strategies, and often lacks the incorporation of real-time, data-driven analytical models.

Moreover, a large segment of current literature continues to rely on conventional statistical approaches or simple regression-based techniques. While these methods help in understanding general trends, they are typically inadequate for capturing the sequential dependencies and non-linear patterns that are common in practical supply chain environments. This limitation becomes particularly critical in agricultural supply chains, where unpredictable changes in weather, seasonality, and market demand are frequent and can significantly impact operations.

There is limited research applying deep learning models such as Long Short-Term Memory (LSTM) networks to the tea supply chain. LSTM is known for its ability to capture long-range dependencies in time-series data, making it a strong candidate for forecasting supply and demand. Despite its potential, its application within the context of the tea industry remains minimal. Furthermore, the combination of LSTM-based forecasting with real-time deployment platforms such as Flask web applications is even more rarely explored in existing studies.

Another key gap is the lack of end-to-end implementation frameworks in the literature. Many studies emphasize the accuracy or performance of prediction models but do not translate these findings into practical, operational tools that supply chain managers can readily use. Our group research addresses this limitation by applying an LSTM model to real-world data obtained from the Watawala Tea Factory and by developing a user-friendly interface for practical, operational use.

Research Gap Comparison – Logistics Management

Study	Focus on Tea Industry	Advanced Model	Real World Data Used	Practical implementation	Interactive Interface
Research A	✗	✗	✓	✗	✗
Research B	✗	✗	✓	✗	✗
Research C	✓	✗	✓	✗	✗
Research D	✗	✓	✓	✗	✗
Proposed System	✓	✓	✓	✓	✓

The table above compares the key features of relevant studies in predictive analytics in agriculture with the scope of our research. Each column outlines essential elements such as the focus on the tea industry, the use of advanced models like LSTM, incorporation of actual industry data, practical application, and the presence of an interactive interface. A tick (✓) indicates the presence of a feature, while a cross (✗) denotes its absence. As shown, most existing studies either do not employ deep learning models or fail to use real-world data from the tea sector. Additionally, many of these works remain theoretical and do not result in full-scale, operational systems. In contrast, our research closes these gaps by integrating real factory data, utilizing the LSTM model, and implementing a fully functional system with an interactive, Flask-based interface to support real-time supply chain forecasting.

1.3 Research Problem

The global tea market, with Sri Lanka's renowned tea industry at its heart, is increasingly grappling with a multitude of complex challenges that threaten its stability and growth. These challenges stem from a volatile and unpredictable operating environment characterized by fluctuating demand patterns, frequent disruptions within the supply chain, and an unstable labor force. Various macroeconomic influences, including changing global trade dynamics and price volatility, intersect with environmental pressures such as irregular weather conditions, the intensifying impacts of climate change, and seasonal variations in production capacity. Adding to this complexity are evolving consumer preferences that demand not only quality but also sustainability and traceability, along with pronounced regional disparities in both the supply of tea leaves and consumer demand. This intricate web of factors collectively creates an environment of heightened uncertainty for stakeholders across the entire tea value chain.

Sri Lanka’s tea industry, globally celebrated for its high-quality Ceylon tea, is deeply reliant on the seamless coordination of an intricate supply chain that spans multiple stages from the initial leaf plucking by laborers in the plantations, through withering and processing at factories, to packaging, quality control, and final export. Each phase of this chain demands precision and timing, as tea leaves are highly perishable and their quality can rapidly deteriorate if delays or mismatches occur. Despite its critical importance, inefficiencies and bottlenecks particularly in the domains of demand forecasting, workforce planning, and inventory management continue to plague the industry. These inefficiencies are not isolated problems; rather, they trigger cascading effects that ripple through the entire supply chain. For instance, inaccurate demand forecasts can lead to overproduction, resulting in surplus inventory that increases storage costs and heightens the risk of leaf spoilage. Conversely, underproduction can cause raw material shortages, forcing disruptions in factory operations and leading to missed orders or compromised product quality.

Labor planning represents another major challenge that is intricately tied to demand fluctuations. Sri Lanka’s tea industry faces persistent labor shortages due to rural-urban migration, an aging workforce, and the seasonal nature of harvesting work. Poor synchronization between labor availability and production schedules leads to missed harvesting windows, reduced yields, and ultimately affects the competitive position of tea producers in global markets. Additionally, logistical delays arising from transportation inefficiencies, traffic congestion, and inadequate infrastructure further exacerbate the supply chain's vulnerability, causing delays in raw material deliveries and finished goods shipments.

Furthermore, the perishable nature of tea leaves amplifies the consequences of any inefficiencies in inventory management. Without precise and timely inventory control, factories are compelled to either hold excessive raw material stocks—risking deterioration and financial losses or maintain insufficient levels that disrupt continuous processing and order fulfillment. These challenges culminate in lost revenue opportunities, diminished product quality, increased operational costs, and a reduced ability to respond swiftly to market changes.

In summary, the sustainability and profitability of Sri Lanka's tea industry depend heavily on overcoming these intertwined challenges by adopting more intelligent, data-driven supply chain management approaches. Improvements in demand forecasting accuracy, labor resource planning, and smart inventory management are not merely operational necessities but strategic imperatives. They are essential to ensuring that the industry remains competitive, resilient, and capable of meeting the evolving demands of global tea consumers while safeguarding the livelihoods of millions who depend on this centuries-old agricultural heritage.

1.3.1. Demand Forecasting

- Traditional Forecasting Methods

Most tea producers still rely on conventional forecasting techniques such as moving averages, regression analysis, and exponential smoothing. While these statistical models are simple to implement, they are ill-suited for capturing the nonlinear, seasonally driven, and multivariate patterns that dominate agricultural production data. These traditional models often assume that future trends mirror historical patterns, ignoring sudden market shifts or environmental anomalies.

This fundamental shortfall causes decision-makers to operate based on inaccurate predictions, leading to operational inefficiencies. For example, overproduction due to demand overestimation results in idle stockpiles and increased warehouse costs, while underproduction during demand peaks can cause customer dissatisfaction, loss of revenue, and reputational damage.

- Lack of External Variable Integration

One of the most critical gaps in existing forecasting solutions is the absence of external variable integration. Tea production and consumption are significantly influenced by factors like precipitation, temperature variations, economic shifts, and regional festivals. However, most current systems fail to incorporate such variables into their forecasting models. This omission results in rigid and simplistic models that cannot adapt to real-world complexities, especially in the face of climate change and market globalization.

- Barriers to Technological Adoption

Despite the proven success of AI and deep learning in fields such as retail forecasting and smart farming, adoption in the tea industry, especially among small and medium-sized enterprises (SMEs)—remains minimal. High initial costs, a lack of technical knowledge, data scarcity, and infrastructure limitations hinder the uptake of modern tools. Furthermore, most AI implementations are theoretical or remain in pilot stages, with very few deployed at a practical, operational level accessible to end users like estate managers or logistics coordinators.

- Need for a Region-Specific, End-to-End, Scalable Solution

Sri Lanka's diverse tea-growing regions have distinct microclimates, soil types, harvesting windows, and consumption behaviors. National-level models or generalized forecasting tools fail to accommodate this regional heterogeneity. What is needed is a customized, end-to-end system that addresses the full spectrum of tea supply chain challenges—from demand forecasting and labor planning to inventory and logistics optimization.

This research proposes a novel AI-powered system, primarily using Long Short-Term Memory (LSTM) neural networks, to model and forecast both demand and labor availability with high granularity. The system will incorporate real-time weather data, historical production statistics, and market demand signals, and will be deployed via an interactive, web-based dashboard (e.g., using Flask and TensorFlow). This tool will be specifically designed for real-time decision-making, offering actionable insights to stakeholders such as tea estate managers, supply chain planners, and policymakers.

1.3.2 Smart Inventory System

The tea supply chain, particularly in Sri Lanka, struggles with managing inventory effectively due to the volatile and seasonal nature of demand combined with the perishability of raw materials. Although monthly demand forecasting using AI models like LSTM has improved accuracy, there is a critical gap in translating these forecasts into actionable, high-resolution (weekly) inventory plans. Current inventory management systems lack dynamic adaptability to real-time variations in demand, labor availability, and supply disruptions. They also insufficiently account for the perishability of tea leaves and sustainability concerns such as minimizing waste and optimizing resource utilization.

This research aims to develop an intelligent AI-driven inventory management system that bridges this gap by converting monthly demand forecasts into precise weekly raw material requirements, integrating real-time data inputs, and addressing operational constraints. Solving this problem is vital to enhancing supply chain responsiveness, reducing waste, lowering costs, and ensuring sustainable production in the tea industry.

Limitations of Conventional Inventory Management

In many tea-producing regions, inventory management remains reactive and manually driven, often relying on spreadsheet-based systems or rigid enterprise resource planning (ERP) tools with limited forecasting capabilities. These systems are typically built around fixed reorder points or historical consumption rates, which fail to account for rapid changes in demand, supply disruptions, or labor availability. Such static models lack the predictive intelligence necessary to proactively plan for weekly fluctuations in raw material needs particularly when the inputs are derived from broad, monthly demand forecasts.

This misalignment between planning granularity and operational frequency creates significant inefficiencies. For instance, weekly overstocking can lead to the spoilage of fresh tea leaves due to their limited shelf life, resulting in waste and increased holding costs. Conversely, understocking during peak periods disrupts production flow, delays order fulfillment, and increases dependency on emergency procurement, which is often more expensive and less reliable.

Disconnect Between Forecasting and Procurement Planning

A critical research gap lies in the disconnect between high-level forecasting outputs and on-the-ground inventory execution. While AI models such as LSTM can provide accurate monthly demand forecasts, there is often no intelligent mechanism in place to decompose these forecasts into operationally useful weekly procurement plans. Without an automated system to bridge this gap, factory managers must manually interpret long-range forecasts and translate them into weekly supply orders an approach prone to human error, inconsistency, and inefficiency.

Moreover, traditional inventory planning methods do not account for variables like lead times, transportation delays, perishability windows, or labor availability. They also fail to dynamically adjust inventory levels in response to external inputs such as weather anomalies, road closures, or harvest disruptions. This results in inventory systems that are both rigid and slow to respond traits that are fundamentally incompatible with the dynamic nature of tea production and distribution.

Need for AI-Driven, Adaptive Inventory Systems

To address these challenges, there is a pressing need for a smart inventory management system that leverages artificial intelligence and real-time data to automatically translate monthly demand forecasts into precise weekly raw material requirements. Such a system must be capable of integrating external factors like weather conditions, labor forecasts, and supply chain disruptions, while also adapting to sudden market changes.

By doing so, tea producers can achieve a more agile and responsive inventory model—minimizing waste, reducing costs, and improving alignment between supply and demand. This level of automation and predictive intelligence is essential for building a resilient and sustainable tea supply chain in the face of ongoing environmental and economic uncertainty.

1.3.4. Labour Shortage

While Sri Lanka's central highlands, especially Watawala, are famous for yielding top-grade Ceylon tea, the area is gripped with a growingly critical issue: a chronic shortage of labor that imperils the productivity and effectiveness of tea estates. The shortage, precipitated by rural-urban migration, an aging population, and the decline of young people's interest in working on plantations, has resulted in considerable operational bottlenecks, particularly during peak plucking seasons. In light of these changing challenges, Watawala's labor management still largely depends on manual, reactive, and obsolete estimation methods not capturing real-time socio-economic and climate dynamics in influencing workforce availability.

Previous work in agricultural AI applications has been largely centered around crop yield prediction, pest management, and soil quality, with very little attention drawn to labor forecasting a vital yet not yet adequately explored aspect of tea cultivation. Furthermore, existing models tend to be too one-size-fits-all and are not region-specific in their adaptability for localized settings such as Watawala, where weather patterns, estate-specific labor patterns, and rolling production requirements call for a more localized and data-oriented approach.

Above all, there is an evident lack of sophisticated systems with short-term labor forecasting integrated with multidimensional data like localized weather conditions (e.g., rainfall, temperature), estate-level business cycles, and market-based production calendars. There isn't any existing model that provides real-time indications of labor surplus or deficit situations, nor do they give actionable input on anticipating proactive workforce planning and supply chain coordination.

This absence of AI-driven, local, and time-sensitive labor forecasting models is a research deficit at its core. Closing this gap has the ability to transform labor management from an intuitive, response-based endeavor to a predictive, optimized process with express alignment to the specific socio-economic and climatic nature of tea estates in Watawala. By tapping into deep learning algorithms such as Long Short-Term Memory (LSTM) networks and integrating them into cloud-based, decision-support platforms, this study bridges an essential gap both in practice and theory facilitating more intelligent, region-targeted labor planning and greatly improving the resilience of one of Sri Lanka's most critical agricultural supply chains.

1.3.1 Logistics Management

The tea industry, particularly in Sri Lanka, remains a crucial pillar of both the national economy and the agricultural sector. Despite its significance, the industry continues to struggle with long-standing inefficiencies across its supply chain. These inefficiencies present themselves in various ways, including inaccurate demand forecasting, delays in logistics, increased operational costs, and poor inventory control. A major contributing factor to these challenges is the limited use of real-time data and advanced predictive technologies that could support more informed and timely decision-making. Without the ability to forecast supply and demand accurately, stakeholders often experience either overproduction—resulting in waste and excess cost—or underproduction, which leads to unmet demand and lost business opportunities.

One of the central issues in the tea supply chain is the reliance on traditional forecasting methods, which primarily use historical data and manual judgment. While these approaches offer some value, they often fall short when confronted with the unpredictable nature of variables such as climate, shifting consumer trends, and changes in global demand. Additionally, the tea industry is characterized by seasonal fluctuations that impact both production volumes and market demand, making it even more difficult to develop reliable forecasting models. In the absence of predictive systems that can adapt to these complexities, tea producers and supply chain managers frequently face delays and inaccuracies in their planning and operations.

Alongside forecasting challenges, logistics and transportation within the tea supply chain face notable inefficiencies. Issues such as inefficient route planning, unexpected delays, and inadequate inventory oversight are common. These problems become particularly pronounced during peak seasons when the pressure to meet heightened demand intensifies. Many tea producers still rely on manual tracking systems or outdated logistics software, making it difficult to ensure timely deliveries and proper stock distribution. This not only affects supply chain efficiency but also undermines the ability to respond swiftly to changing market conditions.

While some advancements have been made toward automation and digital optimization in agriculture, most existing systems within the tea sector are either overly simplistic or fail to incorporate modern technologies such as machine learning and real-time analytics. Although there have been isolated efforts to modernize certain components of the supply chain, there is a noticeable gap in the use of advanced deep learning techniques—especially Long Short-Term Memory (LSTM) networks—for demand forecasting and logistics optimization in tea production and distribution.

The core research problem addressed by this study is the absence of an integrated, data-driven framework that unites predictive modeling, real-time data processing, and practical, actionable insights tailored specifically for tea supply chain optimization. While various forecasting and optimization methods exist, they often lack the flexibility and intelligence required to handle the unique complexities of the tea industry. Our research aims to meet this need through the development of a comprehensive system that can:

- Improve Demand Forecasting: Develop an accurate, machine learning-based forecasting model using time-series data, with a particular focus on LSTM networks to better predict tea demand.
- Optimize Supply Chain Logistics: Combine predictive forecasting with real-time logistics data to enhance route optimization, minimize delays, and improve inventory management.

- Real-Time Data Integration: Deliver a data visualization interface that enables stakeholders to make real-time adjustments to supply chain operations based on current data trends.
- Practical Implementation: Build a fully integrated and user-friendly system using Python libraries such as Flask, TensorFlow, and Pandas, and deploy it as a web-based application. The solution is designed for use at the Watawala Tea Factory and has the potential to scale across the broader tea industry.

Through these objectives, our research seeks to bridge the gap between traditional tea supply chain practices and modern, data-centric solutions. The combined application of LSTM models for forecasting and Flask-based deployment for real-time interaction introduces a new level of functionality for operational decision-making. Additionally, the integration of tools such as Pandas for preprocessing, Matplotlib for visualization, and Google Colab for model training enhances both the reliability and accessibility of the solution.

Ultimately, this research contributes to the tea industry by delivering a practical, data-driven tool that supports improved forecasting, logistical efficiency, and operational sustainability. The proposed system has the potential to reduce costs, streamline supply chain activities, and provide a scalable blueprint for digital transformation in tea production and distribution.

1.4 Research Objectives

1.4.1 Main Objective

1. **AI-Based Demand Forecasting using LSTM**

The primary objective of this research is to design and implement an AI-powered demand forecasting model utilizing Long Short-Term Memory (LSTM) neural networks to optimize the Sri Lankan tea supply chain. The goal is to tackle the issue of demand unpredictability by producing accurate and timely monthly forecasts, which are critical for efficient planning in production, procurement, and distribution. Traditional statistical methods often fail to capture complex temporal dependencies and nonlinear trends, especially in agricultural domains with seasonality and external factors [10].

This LSTM-based forecasting model is trained on historical demand data alongside external variables such as rainfall, temperature, and market activity. The model's ability to remember long-term patterns makes it highly suitable for identifying latent trends in tea consumption and demand[9]. Stakeholders, including estate managers, distributors, and policymakers can use the output of this system to anticipate market needs and align their resources accordingly. As a result, the forecasting system is expected to improve synchronization across supply chain nodes, reduce waste, and enhance economic sustainability within the tea industry.

2. AI-Driven Inventory Management System

This objective focuses on the development of an AI-based inventory management system that leverages demand forecasts to predict the weekly requirement of raw materials, particularly fresh tea leaves. In the tea industry, the perishable nature of the raw materials necessitates precise inventory control to prevent spoilage and resource wastage. The system bridges the gap between forecasted monthly demand and real-time operational decisions by using predictive analytics to manage short-term procurement and stock levels.

The integration of real-time monitoring tools and automation allows the system to dynamically adjust inventory recommendations based on fluctuations in demand, supplier reliability, and harvesting conditions. This predictive inventory system is especially beneficial for small and medium-sized enterprises (SMEs) that lack the infrastructure for advanced planning. By automating procurement decisions and synchronizing them with predicted demand, the system reduces excess inventory costs, enhances responsiveness, and contributes to the overall resilience and cost-effectiveness of the supply chain

3. Logistics Optimization in the Tea Supply Chain

The fourth key objective of the research is to enhance the efficiency of transportation and logistics in the tea supply chain through machine learning techniques, with a focus on reducing delivery costs and optimizing transport routes. Logistics plays a pivotal role in ensuring timely delivery of tea products from estates to factories and export hubs. However, inefficiencies in scheduling and routing often lead to increased fuel consumption, delays, and higher operational costs, especially in hilly terrains like Watawala.

By analyzing historical delivery schedules, demand distribution, and geographic data, an LSTM-based model is employed to predict when and where tea products are most likely to be required. This allows logistics teams to plan more efficient delivery routes and vehicle allocations. Advanced tools such as TensorFlow and Pandas are used for model development, while a web-based interface built with Flask enables visualization and interaction with real-time logistics insights. The system's predictive capability supports data-driven decision-making and reduces unnecessary trips, contributing to more sustainable logistics operations across the tea supply chain.

4. **LSTM-Based Labor Availability Forecasting for Watawala**

The overall objective of this research is to design and implement an AI-powered forecasting system for accurately predicting short-term labor availability in the Watawala tea supply chain in Sri Lanka. This project addresses the key issue of labor shortage by offering a predictive, data-driven solution that enables proactive decision-making in estate management. The suggested system leverages Long Short-Term Memory (LSTM) neural networks that are well-suited for acquiring knowledge of time-dependent relationships between labor patterns, climatic conditions, and levels of production demand. The model will forecast the availability of labor in the key estate areas for a week, providing estate managers with valuable information for better scheduling of the workforce.

Aside from the forecasting of labor supply, the research likewise aims to juxtapose the equilibrium of projected labor availability and forecasted labor demand based on raw tea leaf plucking requirements. By integrating expected levels of production, plucking levels, and demand factors, the system identifies periods of likely labor surplus or shortage. Such advance knowledge enables strategic allocation of manpower resources, reduces delays in harvesting, minimizes crop wastage, and ensures less turbulent business flow along the supply chain of tea. A further objective of this study is to develop a region-specific, scalable prediction system that responds to the individualized nature of Watawala's tea estates estate-specific work patterns, localized climatic influences, and seasonality in crop cycles. Unlike conventional AI methods superimposing generalized models on agricultural problems, this system will be grounded in the nuances of the local context, making it more applicable and reliable in day-to-day estate planning.

Lastly, the forecasting system will be incorporated into a cloud-based centralized platform that can be accessed through an easy-to-use web interface. This provides real-time access to forecasts and labor analysis for decision-makers, supervisors, and planners. Through the integration of artificial intelligence, localized data modeling, and user-friendly deployment, the research makes theoretical as well as practical contributions to the development of intelligent labor planning in Sri Lanka's tea industry towards enhancing resilience, efficiency, and sustainability of supply chain operations.

1.4.2 Specific Objectives

This research aims to improve demand forecasting, labor prediction, inventory management, and delivery efficiency in the Sri Lankan tea industry by leveraging advanced Artificial Intelligence techniques—specifically Long Short-Term Memory

(LSTM) neural networks. The following specific objectives have been identified to achieve this aim:

1. To develop an AI-powered demand forecasting system using LSTM models

The first objective is to design and implement a demand forecasting model that utilizes LSTM neural networks to accurately predict the future demand for tea products produced by the Watawala Tea Factory. Historical sales data over several years will be collected and analyzed to identify patterns and seasonality. Furthermore, external variables such as weather conditions (rainfall, temperature, humidity), holidays, regional festivals, market trends, and promotional activities will be incorporated as input features to improve forecast precision [6]. The forecasting system will be trained and tested using performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to ensure accuracy and reliability. This will enable the factory to make informed decisions on production planning, packaging, and distribution.

2. To design and implement an intelligent inventory management decision-support system

This objective involves creating a data-driven system that assists in monitoring, forecasting, and optimizing inventory levels of raw materials, packaging supplies, and finished tea products. By integrating historical usage patterns, current stock levels, production forecasts, and anticipated market demand, the system will use AI techniques to model inventory dynamics. It will help in determining optimal reorder points, safety stock levels, and procurement schedules. Furthermore, the system will provide real-time recommendations and alerts to minimize the risks of overstocking and stockouts, ensuring smooth production continuity and minimizing inventory-related costs.

Visualization tools such as dashboards and graphs will be incorporated to help stakeholders easily interpret inventory trends and make informed decisions.

3. To build a labor forecasting model based on historical and real-time data

The second objective focuses on forecasting the availability and requirement of labor resources within the Watawala region. Tea production, especially during harvesting periods, is labor-intensive and highly sensitive to worker availability. The model will use historical labor attendance records, task completion logs, seasonal labor demand cycles, and environmental data such as weather forecasts and terrain conditions that can influence worker availability. By applying LSTM models to this multidimensional dataset, the system will predict future labor needs and potential shortages, allowing management to take proactive steps such as adjusting work schedules or arranging supplementary labor. This will help avoid bottlenecks in production due to labor shortages.

4. To develop a traffic prediction model for optimizing delivery schedules and routes

The final objective focuses on enhancing the efficiency of tea product delivery by predicting traffic conditions that may affect transportation routes. Historical traffic datasets from major delivery routes in and around the Watawala region will be analyzed along with real-time inputs such as roadwork notifications, weather forecasts, and public holidays. LSTM-based models will be trained to forecast traffic congestion levels during different times of day and week. Based on these predictions, the system will generate optimized delivery routes and schedules, ensuring timely distribution of tea products to markets and minimizing delays, fuel consumption, and operational costs. This will contribute to improved customer satisfaction and supply chain performance.

2 METHODOLOGY

2.1 Demand Forecasting

The system design phase follows, where the architecture, modules, data flow, machine learning pipeline, and user interfaces are mapped out. Then, data acquisition is carried out to collect relevant datasets such as historical tea demand, weather data, and market indicators. High-quality, diverse data ensures the model can learn accurate demand patterns.

Once the data is acquired, it undergoes data preprocessing, which includes cleaning, handling missing values, noise reduction, normalization, and splitting into training and testing sets. Feature engineering is also conducted to highlight important attributes[7].

In the model training phase, an LSTM-based machine learning model is trained using the preprocessed dataset. This involves optimizing hyperparameters, managing sequential data dependencies, and ensuring accurate temporal representation.

The evaluation and tuning phase then measure the model's performance using metrics such as RMSE, MAE, and MAPE. Based on the evaluation, the model is fine-tuned for improved generalization and robustness[8].

Finally, the model is deployed in a user-accessible system. Deployment involves integrating the model with a cloud-based platform, enabling real-time predictions, and providing access through intuitive web dashboards and APIs. The system ensures long-term functionality with adaptability to changing data trends and business requirements.

Additionally, a decision support tool is constructed to provide day-ahead forecasts of labor availability and excess-deficiency reports. The tool helps estate managers view forecasts, track daily labor availability, and make data-driven decisions on workforce allocation. It enhances operational efficiency and strategic labor planning across the supply chain.

Requirement Analysis

In the initial phase of the project, the primary objective was to identify both the business and technical requirements necessary for developing an LSTM-based forecasting system specifically tailored to the Sri Lankan tea industry. A combination of qualitative and quantitative methods was employed to collect comprehensive information. Stakeholder interviews were conducted with key individuals such as estate managers, production supervisors, supply coordinators, and exporters to gain insights into the current forecasting practices, existing challenges, and expectations from an advanced forecasting system. A common theme across these discussions was the demand for an automated solution capable of accounting for seasonality, weather variability, and global market trends[11]. To complement the interviews, structured questionnaires were distributed to a broader audience to gather data on forecasting frequency, current data-tracking practices, digital tool adoption, and how forecast results influence operational decisions. The responses confirmed and enriched the findings from the interviews, supporting data-driven design choices. Additionally, an in-depth literature review was conducted, analyzing previous forecasting models, agricultural systems, and industry publications, which highlighted the advantages of using LSTM models due to their strength in handling temporal dependencies and sequential data. Based on these findings, both functional and non-functional requirements were defined. Functional requirements included the ability to input historical data, generate demand forecasts, provide visualizations, and enable report downloads. Non-functional requirements focused on ensuring high accuracy, scalability, responsiveness, user-friendliness, and data security. The results of this phase were documented in a detailed requirement specification report, which served as a critical reference for aligning stakeholder expectations and guiding the design and development phases of the system[12].

System Design

The system is architected as a modular, scalable, and cloud-based platform comprising data ingestion, preprocessing, model training, evaluation, and a user-friendly web interface. The backend includes the LSTM model pipeline, while the front end displays interactive charts, forecasts, and labor availability status.

APIs are used to connect different components, ensuring flexibility and easy maintenance. Cloud integration ensures real-time accessibility for stakeholders, enhancing collaborative planning and operational agility.

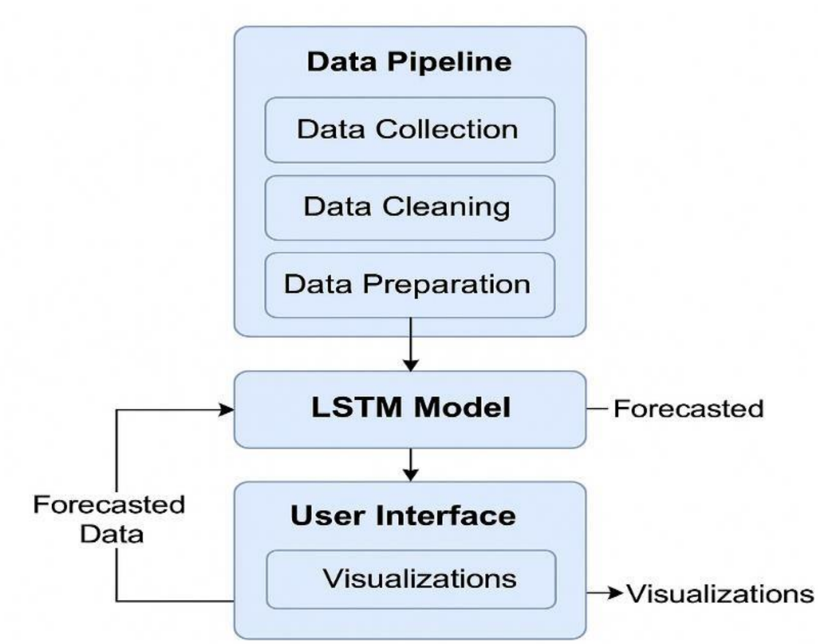

Figure 2.1 System Overview Demand Forecasting

Data Collection and Preprocessing

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 [].

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 timeseries 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 [13].

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 Demand Forecasting

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 timeseries 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.

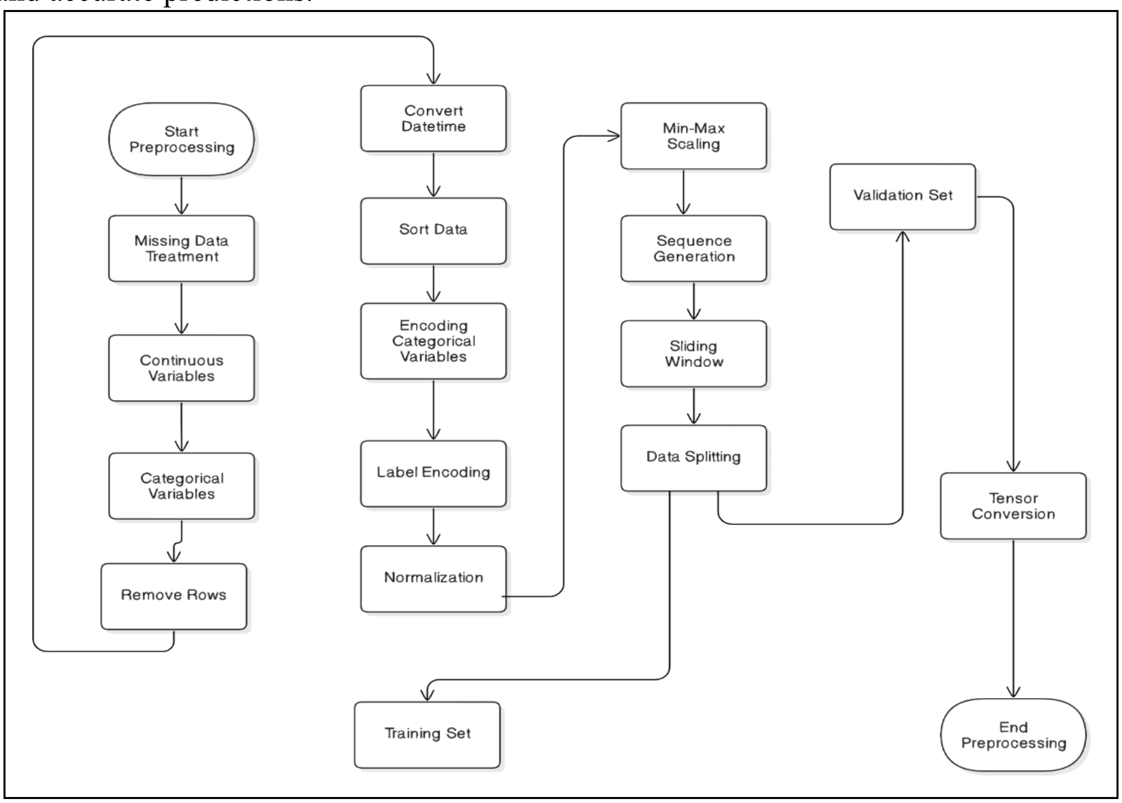

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Figure 2.3 : Data preprocessing Overview Demand Forecasting

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 longterm 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 decisionmaking in the supply chain in the tea industry.

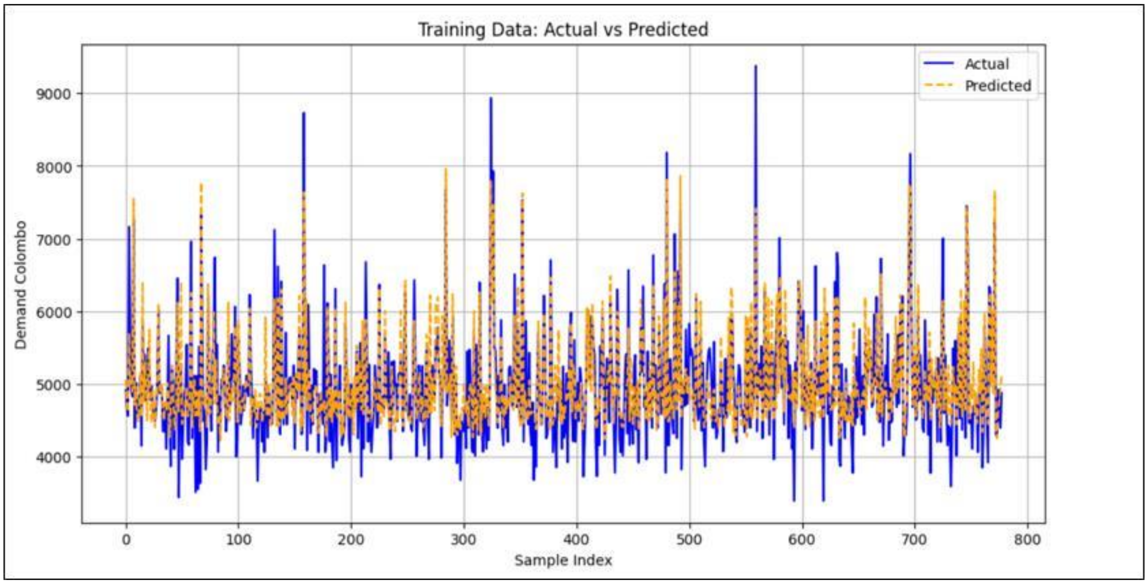


Figure 2.4 : Model Training Vs Actual Demand

Testing and Validation

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 tradeoff 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.

System 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 onpremises 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.

Commercialization

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 demandsupply 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.

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.

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 2-1 Summary SWOT Analysis of the Demand 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.

Implementation and Testing

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.

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.

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.

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 2-2 Test Cases Summary Demand

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 highload conditions	Simulate large volumes of data or unexpected disruptions to assess model stability.

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.

2.2 Smart Inventory Management

The development of the smart inventory management system follows a carefully orchestrated methodology designed to enhance the efficiency and responsiveness of tea supply chain operations. The process begins with the conceptualization and design of the system architecture, outlining the flow of data, functional modules, and user interaction points. Once the structure is established, a comprehensive data acquisition phase is undertaken to gather a wide range of inputs these include historical records of tea sales, meteorological data such as rainfall and temperature, and labor force statistics that influence both supply and operational capacity. After collection, the data undergoes rigorous preprocessing to ensure quality and reliability. This involves cleansing the data to remove inconsistencies, filling in missing values, normalizing features for uniformity, and extracting relevant patterns through feature engineering. These curated datasets are then used to train a Long Short-Term Memory (LSTM) neural network—a deep learning model adept at recognizing long-term trends and time-dependent patterns. The model is specifically tailored to translate monthly demand forecasts into precise weekly raw material needs, supporting timely and accurate inventory planning. To ensure robust performance, the model’s predictions are assessed using industry-standard metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Based on these evaluations, the model is fine-tuned to optimize prediction accuracy and generalization capabilities across varying scenarios.

In the deployment phase, the trained model is integrated into a cloud-based ecosystem that supports scalability, real-time access, and remote usability. A dynamic web-based dashboard is developed as the user interface, enabling tea estate managers and supply chain stakeholders to visualize demand forecasts, monitor inventory flows, and anticipate labor needs. Additionally, the system incorporates a decision support module that provides day-ahead labor availability forecasts and highlights any anticipated surpluses or shortages. This integration empowers managers to make proactive, data-driven decisions that reduce waste, avoid production disruptions, and enhance the overall agility and sustainability of tea operations.

Requirement Analysis

The requirement analysis phase serves as the foundation for developing a robust Smart Inventory Management System tailored to the operational needs of the tea industry. This stage involves identifying both functional and non-functional requirements by engaging with stakeholders such as factory managers, supply chain planners, IT staff, and field supervisors. The primary functional requirement is the ability to forecast weekly raw material needs based on historical monthly demand, weather variations, and labor availability. The system must also support real-time inventory tracking, generate automated alerts for shortages or surpluses, and provide actionable insights for production planning and workforce deployment.

To ensure data-driven decision-making, the system must integrate with external data sources including weather APIs, enterprise resource planning (ERP) systems, and labor attendance databases. Additionally, the requirement analysis outlines the need for a user-friendly web dashboard capable of visualizing trends, predictions, and inventory health in an intuitive format. Non-functional requirements such as system scalability, data security, cloud compatibility, and low-latency performance are equally important, as the system must remain reliable under varying data loads and operational conditions.

Special consideration is also given to adaptability and future extensibility, allowing the system to evolve with changes in tea production cycles, labor patterns, and market dynamics. Overall, the requirement analysis ensures that the smart inventory system is not only technically sound but also aligned with the strategic and operational objectives of the Sri Lankan tea industry.

Functional Requirements

- Inventory Monitoring
- Data Integration
- Visualization Dashboard
- User Role Management

Non – Functional Requirements

- Scalability
- Reliability
- Performance and Speed
- Security
- Usability
- Maintainability
- Portability and Accessibility
- Data Accuracy and Consistency

System Design

The Smart Inventory Management System is designed as an intelligent, modular, and cloud-enabled solution that integrates machine learning, real-time analytics, and user-centric dashboards to address the specific needs of the tea production industry. The system architecture is divided into key functional layers: data acquisition, preprocessing, machine learning forecasting, decision support, and user interface. It begins with a data ingestion layer that systematically collects and aggregates diverse datasets, including historical monthly tea demand, weather information (such as rainfall), and labor availability records from estate databases and public APIs.

Once collected, the data passes through a preprocessing stage where it is cleaned, normalized, and structured to ensure consistency. Missing values are handled using interpolation techniques, outliers are filtered, and key features are engineered to highlight influential variables. This refined data is fed into an LSTM-based forecasting model, which is especially suited for time-series analysis. The LSTM model is trained to detect long-term dependencies, seasonality, and dynamic trends in the data, and then used to generate accurate weekly raw material forecasts from historical monthly demand.

Model performance is rigorously evaluated using error metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), and the model is fine-tuned accordingly to maximize forecasting precision. The prediction results are then passed to a decision support module, which interprets them to highlight potential inventory gaps, overstock risks, or raw material shortfalls. This module also includes labor forecasting to help in optimizing workforce planning based on predicted demand and weather disruptions.

The final layer is a responsive, web-based dashboard designed with usability and clarity in mind. It allows factory managers, supervisors, and planners to interact with real-time data through intuitive graphs, alerts, and downloadable reports. The system is deployed via a cloud platform to ensure scalability, high availability, and real-time data syncing across multiple stakeholders. It is also designed to integrate seamlessly with existing ERP and supply chain systems, enabling data-driven, agile, and sustainable operations across the entire tea supply chain.

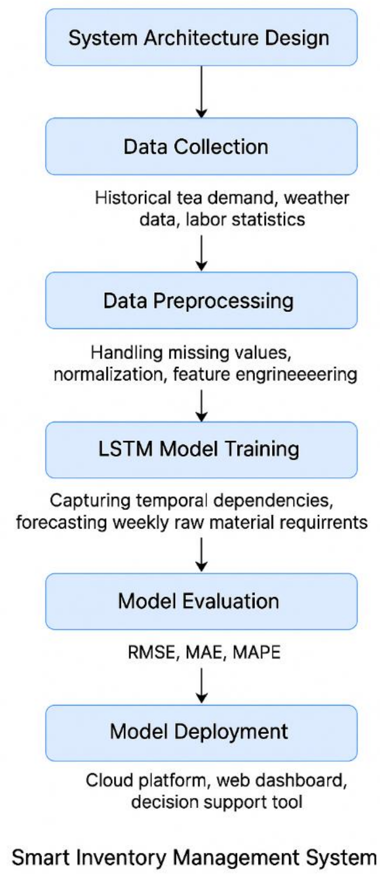


Figure 2.5: System Overview of Smart Inventory Management

Data Collection

The data collection phase is a critical backbone of the Smart Inventory Management System, as it directly influences the precision of demand predictions and inventory control mechanisms. This process begins with the acquisition of historical monthly sales data from the Watawala Tea Factory, which serves as the primary input for forecasting raw material requirements. To accurately transform monthly demand into weekly consumption patterns, detailed weekly-level production logs and inventory movement records are collected. These data points help the system learn typical intra-month consumption behaviors and identify variations caused by operational shifts or seasonal trends.

In addition to production data, the system integrates weather data including rainfall, temperature, and humidity sourced from local meteorological departments, given their impact on both raw tea leaf availability and processing capacity. Labor availability records are also collected to assess workforce fluctuations that may affect procurement, plucking cycles, and inventory turnover rates. These include attendance reports, shift schedules, and labor supply trends across different seasons.

All datasets are cleaned, time-aligned, and structured into a unified format for training the LSTM model. By combining internal operational metrics with external influencing variables, the data collection framework ensures a high-fidelity representation of real-world conditions. This enables accurate weekly demand prediction and supports a responsive, just-in-time inventory strategy that minimizes waste and overstocking.

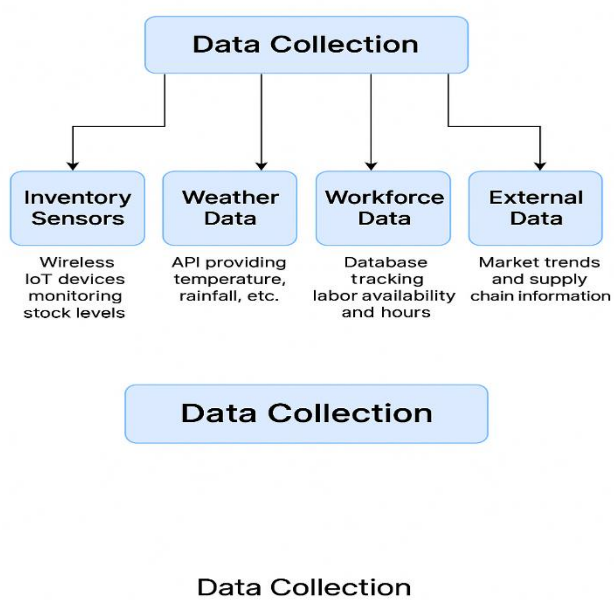


Figure 2.6: Data Collection Overview of the Smart Inventory Management

Model Training

The model training phase is the core computational component of the Smart Inventory Management System, designed to learn complex temporal relationships between historical sales patterns, environmental factors, and inventory usage. Using the cleaned and preprocessed dataset, which includes monthly sales figures, weekly raw material usage, weather conditions, and labor availability, a Long Short-Term Memory (LSTM) neural network is selected due to its effectiveness in modeling time-series data with long-term dependencies.

The data is divided into training and validation sets, ensuring the model learns from past behavior while being evaluated on unseen patterns. Key steps in this phase include sequence generation (turning the time-series data into input-output pairs suitable for LSTM), normalization (scaling data to improve convergence), and hyperparameter tuning (adjusting layers, learning rate, batch size, etc.) to maximize predictive accuracy.

The model is trained iteratively using backpropagation through time (BPTT), optimizing the network to minimize loss functions such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Regularization techniques like dropout and early stopping are used to prevent overfitting. During training, the model learns how monthly demand patterns translate into weekly raw material needs, factoring in variables like climate and labor fluctuations.

Upon completion, the trained LSTM model demonstrates its ability to forecast future weekly inventory requirements with high reliability. This prediction capability is crucial for enabling timely procurement and efficient resource allocation in the tea production supply chain.

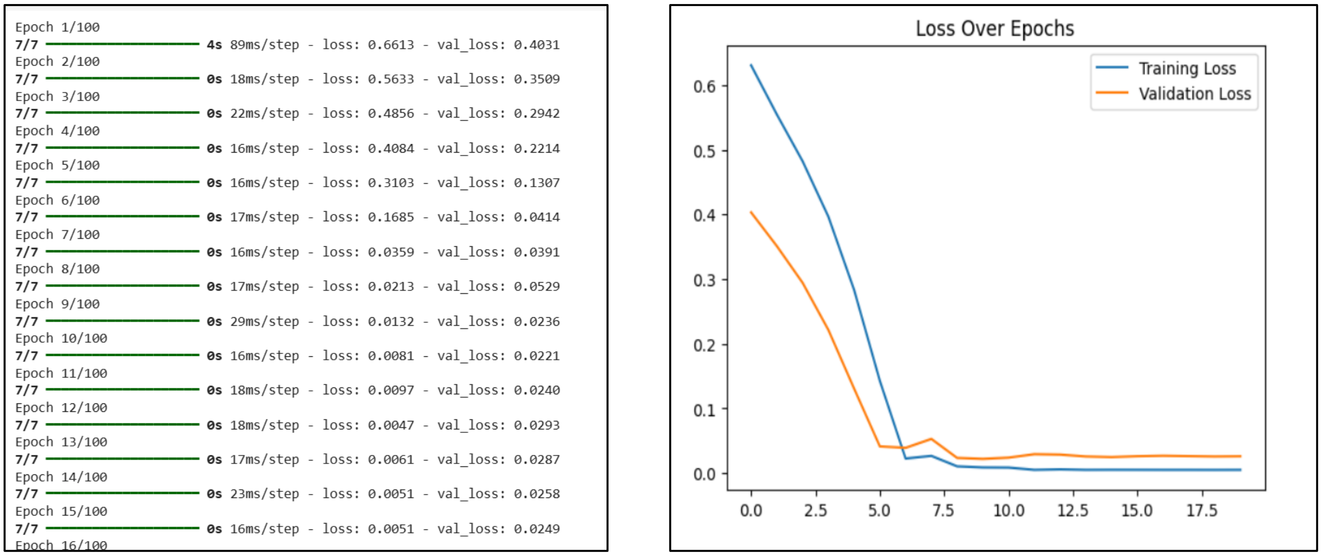


Figure 2.7: Overview of model training and loss graph

Testing & Validation

The testing and validation phase play a crucial role in confirming the effectiveness, accuracy, and reliability of the LSTM-based smart inventory management system before real-time deployment. After the model has been trained on historical data (including monthly sales, weather, and labor availability), it is subjected to rigorous evaluation using a holdout test dataset that the model has not seen during training. This ensures that the forecasting system is not just memorizing patterns but is capable of generalizing its predictions to new, unseen scenarios.

The validation process begins by calculating multiple statistical error metrics to quantify prediction accuracy. These include:

- Root Mean Square Error (RMSE): Measures the square root of the average squared differences between actual and predicted values, capturing large errors more severely.
- Mean Absolute Error (MAE): Reflects the average magnitude of errors without considering direction, providing a straightforward accuracy measure.

- Mean Absolute Percentage Error (MAPE): Expresses prediction errors as a percentage, making it easy to interpret across varying demand volumes.

Each of these metrics offers insight into different aspects of the model’s performance—ranging from sensitivity to outliers to average deviation across time intervals. For weekly raw material forecasting, low values in these metrics indicate the model’s capability to adapt to real-time fluctuations in demand.

In addition to numerical testing, graphical validation is performed by plotting the predicted weekly raw material needs alongside actual historical consumption. This helps stakeholders visualize how closely the model follows real-world trends, including seasonal shifts, demand spikes, and off-peak periods.

To assess the temporal stability and robustness of the model, techniques such as k-fold cross-validation and walk-forward validation are used. These methods test the model's consistency across different segments of the time-series data and help prevent overfitting.

Beyond the machine learning component, system-level validation is conducted. This involves testing whether the forecasted outputs are correctly interpreted and utilized by the inventory module. The system is subjected to simulated scenarios such as sudden weather anomalies, labor disruptions, and festival seasons to ensure it can still deliver practical and adaptive recommendations.

Furthermore, the integration between the forecasting model and the cloud-based dashboard is verified. Functional testing confirms that users can access weekly predictions in real-time, interact with forecast visualizations, and receive alerts or recommendations when potential shortages or excess inventory situations are predicted.

Overall, the testing and validation phase ensures that the smart inventory management system is not only statistically sound but also operationally reliable, adaptable, and usable in real-world tea supply chain conditions.

System Deployment

The deployment phase of the Smart Inventory Management System represents the final and most critical step where all developed components—data pipelines, predictive models, interfaces, and analytics modules are integrated into a unified, operational platform. This ensures the system becomes not only functional but also accessible and actionable for end-users, primarily tea estate managers, inventory controllers, and supply chain coordinators.

The process begins by containerizing the LSTM forecasting model, typically using Docker, and deploying it to a scalable cloud infrastructure such as AWS EC2, Google Cloud Platform, or Microsoft Azure. This environment provides computational resources needed for real-time inference and supports continuous model retraining as new data becomes available. Kubernetes or other orchestration tools may be used to manage and scale multiple service instances, ensuring fault tolerance and high availability. The cloud-hosted model is then connected to a centralized web-based dashboard through secure APIs. This dashboard is designed to be intuitive and interactive, offering real-time visualizations of predicted weekly raw material requirements, historical sales trends, labor availability insights, and inventory health indicators. It serves as a comprehensive decision-support interface where users can configure thresholds, receive alerts, and generate automated reports.

To support dynamic inventory management, the system incorporates a rules engine that cross-references predicted demand with current stock levels and triggers procurement actions, reorder suggestions, or redistribution plans. These decisions can also be forwarded to integrated ERP or supply chain management systems via middleware, enabling seamless coordination between forecasting, procurement, and logistics operations.

Security is a critical component of deployment. The platform implements role-based access control (RBAC), user authentication (via OAuth or SAML), and encryption (both in transit and at rest) to safeguard sensitive business and operational data. Additionally, a logging and monitoring subsystem tracks all activities, generates usage analytics, and flags anomalies for quick intervention. Backup and recovery protocols ensure business continuity in case of system failure or data corruption.

As part of deployment, a feedback loop is also established, enabling users to annotate inaccuracies in forecasts or flag unexpected disruptions (e.g., sudden labor strikes, rainfall anomalies). These inputs are used to improve model performance over time through periodic retraining. Scheduled evaluations ensure the system maintains a high level of accuracy and relevance as operational conditions evolve.

In essence, this deployment approach transforms the AI-driven inventory forecasting model into a robust, cloud-native platform that supports real-time visibility, predictive analytics, and intelligent decision-making. By bridging predictive insights with operational execution, the deployed system becomes a vital tool in driving supply chain resilience, minimizing waste, and enhancing overall productivity in Sri Lanka’s tea industry.

Commercialization

The commercialization phase for the Smart Inventory Management System (SIMS) focuses on transforming the system from a research-based prototype into a commercially viable, scalable, and industry-ready solution. The strategy encompasses market positioning, pricing structure, deployment readiness, and partnership development to ensure the solution can be widely adopted by the agricultural sector, particularly the tea industry.

SIMS is positioned as an AI-powered inventory planning and raw material forecasting solution tailored to address three key market segments: tea estate managers, supply chain operators, and agribusiness software vendors. Each segment is targeted with a unique value proposition. Tea estate managers are offered predictive insights to optimize procurement and reduce overstocking or understocking. Supply chain coordinators benefit from improved planning, synchronized production cycles, and reduced lead times. For agri-tech vendors, SIMS functions as a white-label integration that enhances their digital agriculture solutions with intelligent forecasting capabilities.

To cater to different scales of operation, a tiered subscription pricing model was designed. For small and medium-scale estates, a cost-effective monthly subscription model is offered based on the number of forecasted SKUs and volume handled. For enterprise clients such as large conglomerates or plantation groups, custom enterprise licensing is available, which includes API access, integration support, cloud deployment, and dedicated customer service.

As part of its market penetration strategy, SIMS establishes partnerships with tea industry associations, local government agricultural departments, agri-tech startups, and ERP solution providers. These partnerships ensure that SIMS can integrate with existing systems and gain access to shared datasets, enhancing its accuracy and relevance.

Commercial deployment is supported by a cloud-based infrastructure with a responsive web interface, role-based access control, and a multilingual dashboard. The platform supports seamless scalability and geographic expansion, enabling deployment across multiple regions or factories with minimal configuration effort. User support mechanisms, including training documentation, onboarding guides, video tutorials, and regional language support, have been established to promote easy adoption.

To build market trust and demonstrate efficacy, pilot projects and field trials were conducted in collaboration with selected tea estates in Sri Lanka. These pilots provided real-world validation of the model's ability to predict weekly raw material requirements from monthly demand trends, helping reduce inventory holding costs and improve procurement accuracy.

Marketing and outreach activities included agricultural expos, webinars, journal publications, and workshops in collaboration with agrarian universities. Demonstrations were also given to plantation boards, agribusiness consultants, and logistics providers. These engagements served to build industry awareness, attract early adopters, and gather feedback for iterative improvements.

Through this comprehensive commercialization strategy, SIMS emerges as a scalable, intelligent, and industry-specific inventory management system, built to deliver measurable efficiency improvements in the tea supply chain and lay the groundwork for expansion into other segments of agriculture.

System Architecture

The Smart Inventory Management System is architected as a modular, cloud-integrated solution designed for scalability, real-time data processing, and predictive analytics. At its core, the architecture consists of four key layers are Data Ingestion Layer, Processing & Forecasting Layer, Application Layer, and User Interface Layer.

The Data Ingestion Layer pulls in structured and unstructured data from various sources including monthly sales records, historical inventory levels, weather APIs, labor availability logs, and external market indicators. This data is stored securely in a centralized cloud-based data warehouse. The Processing & Forecasting Layer is powered by a Long Short-Term Memory (LSTM) deep learning model, which is trained to convert monthly demand forecasts into granular weekly raw material predictions. This layer handles data cleaning, feature engineering, temporal pattern analysis, and model optimization. Key components like normalization pipelines, time-window splitting, and seasonality encoding are embedded here. The Application Layer includes inventory logic modules that align predicted demand with procurement needs, generate reorder alerts, and simulate stock-level scenarios under varying supply and demand conditions. It also incorporates a decision support engine that interprets forecast data to generate actionable insights, such as identifying potential raw material shortages. Finally, the User Interface Layer is built as a responsive web dashboard with role-based access. It allows managers to visualize weekly demand trends, inventory projections, procurement schedules, and labor forecasts. The interface supports intuitive charts, downloadable reports, and system notifications to ensure real-time visibility and decision-making.

All components are connected via secure RESTful APIs, ensuring modularity and future extensibility. The architecture supports real-time updates, high availability, and can be deployed across multiple estate locations with centralized control.

Hardware Components

The successful implementation of a Smart Inventory Management System in the tea industry relies heavily on an integrated hardware ecosystem that bridges both on-premise infrastructure and cloud-based technology. At the core of this setup lies the server infrastructure, which includes high-performance cloud servers responsible for hosting the LSTM-based forecasting models. These servers handle large-scale data processing and analytics through robust platforms such as Amazon Web Services (AWS), Microsoft Azure, or Google Cloud, offering scalability, reliability, and seamless access to the forecasting dashboards. In remote plantation areas where network connectivity can be inconsistent, optional edge servers are deployed to ensure uninterrupted data processing and local storage, allowing periodic synchronization with the cloud once connectivity is restored.

To support user interaction and operational oversight, the system includes user interface devices such as desktop computers and laptops, which are used by supply chain managers, inventory controllers, and factory administrators to view real-time data visualizations, reports, and predictions. Additionally, tablets and mobile devices enable field officers and supervisors to remotely access the system, monitor inventory status, and receive alerts, enhancing decision-making agility and responsiveness across the supply chain.

Given the critical nature of continuous system availability, especially in data-sensitive environments, power supply units such as Uninterruptible Power Supplies (UPS) are installed to safeguard servers and edge devices from unexpected power outages, maintaining operational continuity. In rural or off-grid plantation regions, the system is further supported by solar-powered backup solutions, ensuring that energy disruptions do not hinder forecasting accuracy or system access. This hardware architecture creates a resilient, real-time, and scalable foundation for intelligent inventory management tailored to the complex dynamics of the tea industry.

Software Components

The Smart Inventory Management System is powered by a robust software ecosystem that seamlessly integrates forecasting, analytics, user interfaces, and cloud-based services. At its core is the Long Short-Term Memory (LSTM) forecasting engine, developed using Python and deep learning libraries such as TensorFlow or PyTorch. This model is trained to predict weekly raw material requirements based on historical tea sales, weather patterns, and labor availability, capturing temporal dependencies and nonlinear trends with high accuracy. Supporting this model is a data preprocessing and transformation pipeline, built using tools like Pandas, NumPy, and Scikit-learn, which cleans, normalizes, and structures incoming data for efficient model ingestion.

The system’s backend services are developed using frameworks such as Flask or Django, which handle API calls, user authentication, scheduling of model retraining, and integration with external data sources like weather APIs and ERP systems. On the frontend, interactive web dashboards are created using JavaScript, React.js, or Vue.js, along with data visualization libraries such as Chart.js, D3.js, or Plotly. These dashboards provide real-time insights into inventory levels, demand forecasts, and procurement alerts, ensuring usability for both technical and non-technical users.

To manage scalability, data security, and real-time access, the entire platform is deployed on cloud environments such as Amazon Web Services (AWS), Microsoft Azure, or Google Cloud Platform (GCP), leveraging services like AWS Lambda, Azure Functions, or Google Cloud Functions for serverless computing and S3 buckets or Cloud Storage for secure, scalable data management. Additionally, a relational database management system (e.g., PostgreSQL or MySQL) stores structured data such as inventory records, demand history, and user activities.

For communication and alerts, integration with notification systems like Twilio, Firebase, or email APIs enables timely updates to be sent to managers regarding low stock levels, demand surges, or procurement issues. Together, these software components form an intelligent, modular, and scalable system capable of adapting to the dynamic needs of tea production and supply chain management in real time.

Data Flow

The data flow within the Smart Inventory Management System begins with the continuous collection of raw data from multiple sources such as historical tea sales records, real-time weather data, labor availability logs, and existing inventory levels. This incoming data is funneled into a preprocessing module where it is cleaned, formatted, and normalized to ensure consistency and accuracy. The refined dataset is then passed into the forecasting engine specifically, an LSTM-based deep learning model which uses temporal patterns and contextual variables to predict upcoming weekly demand for raw materials. These predictions are then routed to the inventory planning module, which calculates the quantity of raw tea and other resources required to meet forecasted production needs. Simultaneously, the system checks current inventory levels to determine whether there is a surplus or shortfall. Based on this comparison, automated alerts and recommendations are generated for procurement teams, enabling them to initiate timely restocking or reduce excess supply. Finally, all processed data, forecasts, and decision metrics are displayed on a cloud-connected dashboard, accessible through web or mobile interfaces, allowing managers and field officers to monitor inventory health, track demand trends, and take proactive measures all from a unified platform. This streamlined data flow ensures responsiveness, reduces waste, and enhances operational efficiency across the entire tea supply chain.

Security and Privacy

Ensuring the security and privacy of data is a critical component of the Smart Inventory Management System, especially given the reliance on sensitive operational data such as production volumes, labor availability, and sales forecasts. To protect this information, multiple layers of security measures are implemented throughout the system architecture. Data in transit between field devices, local servers, and cloud platforms is encrypted using secure communication protocols like HTTPS and TLS to prevent unauthorized interception. On the cloud server side, strict authentication mechanisms—including multi-factor authentication (MFA) and role-based access controls—ensure that only authorized personnel can access or modify the system’s functionalities. Additionally, sensitive data is stored in encrypted formats using industry-standard encryption algorithms such as AES-256. Regular backups are maintained to prevent data loss, and audit logs are kept to monitor access and changes to the system. Privacy policies are also enforced to comply with regulations such as GDPR and local data protection laws, ensuring that personal or business-critical information is not misused. For further resilience, intrusion detection systems (IDS) and firewalls are deployed to guard against cyber threats, while system updates and patches are routinely applied to mitigate vulnerabilities. These comprehensive security and privacy measures safeguard the integrity, confidentiality, and availability of the system, fostering trust among users and stakeholders.

System Diagram

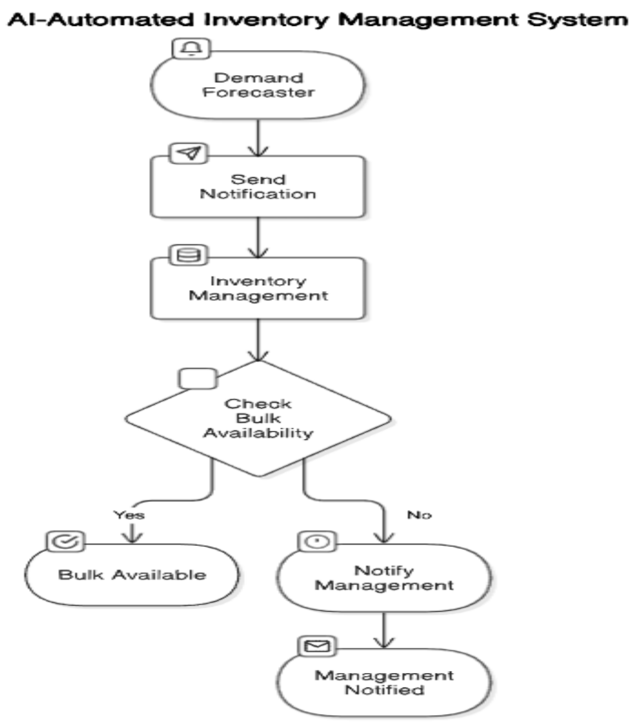


Figure 2.8: Overview of the System Diagram

Interaction Between the Components

The Smart Inventory Management System is designed with a coordinated and intelligent interaction between its hardware, software, and analytical components to ensure optimal inventory control, demand prediction, and labor planning within the tea production supply chain. The system begins with continuous data collection from various sources such as historical tea sales, weather patterns, market indicators, and labor availability records. These inputs are captured through a combination of APIs, manual data entry portals, and IoT-enabled field devices, and are then sent to the cloud-based data storage for centralized access.

Once data is ingested, it is preprocessed within a data management module that handles cleaning, normalization, anomaly detection, and time-series transformation. This cleansed dataset is then fed into the system's machine learning engine, where an LSTM (Long Short-Term Memory) model analyzes the temporal data to forecast weekly raw material needs based on aggregated monthly demand. The model is designed to dynamically adapt to shifting environmental and market conditions by continuously learning from updated datasets. Predictions generated by the model are transmitted to the decision intelligence layer, which interprets the output into actionable inventory and procurement recommendations.

The output from this analysis is then visualized through intuitive dashboards and interfaces accessible to supply chain managers, plantation supervisors, and procurement officers. These interfaces, built using web and mobile applications, provide users with interactive views of inventory levels, predicted shortages or surpluses, and automated alerts for order placements or labor shifts. Additionally, a decision support tool integrated within the system leverages the forecasted data to provide recommendations for daily labor allocation, helping estate managers optimize workforce distribution and avoid delays in plucking or processing.

Throughout the process, all components are in continuous communication via secure APIs and cloud microservices, enabling real-time data flow and decision-making. Edge computing capabilities are optionally employed in rural or low-connectivity regions, ensuring uninterrupted system operation even during internet outages, with periodic synchronization to the cloud. Furthermore, the system includes built-in redundancy and failsafe mechanisms that maintain data integrity and model operation during hardware or network disruptions. Security protocols such as encrypted data transmission, user authentication, and role-based access controls safeguard the system from unauthorized access and data breaches.

In summary, the Smart Inventory Management System functions as an intelligent, self-updating ecosystem where data acquisition, predictive modeling, real-time analytics, and user feedback are tightly integrated. This continuous loop of data flow and response empowers stakeholders across the tea supply chain to make informed, timely, and efficient decisions minimizing waste, reducing costs, and improving overall productivity.

Commercialization Aspects of the Product

Target Market

The initial target market for the Smart Inventory Management System comprises medium to large-scale tea estates and processing factories in Sri Lanka, a country renowned for its Ceylon tea exports. These organizations often struggle with fluctuating demand, labor unpredictability, and inefficient inventory management, making them prime candidates for predictive, AI-driven solutions. In particular, estates operating across multiple regions with decentralized workforce and production units stand to benefit greatly from a centralized forecasting and decision-support tool that aligns raw material procurement with real-time demand trends and labor availability.

As the system matures, the market can be expanded to include other major tea-producing countries such as India, Kenya, Vietnam, and Bangladesh. These countries not only share similar agricultural, labor, and environmental conditions but also face challenges related to seasonal production cycles, climate-induced supply disruptions, and demand volatility in global tea markets. By tailoring the system to local languages, customs, and regulatory standards, the platform can achieve deep penetration across these geographies. Beyond tea, the platform has potential applicability in other perishable and time-sensitive agribusinesses such as coffee, cardamom, black pepper, and tropical fruits—where accurate forecasting and responsive inventory management can significantly reduce spoilage, enhance profitability, and streamline operations.

Institutional buyers such as agribusiness cooperatives, export consortiums, and government-backed agricultural development agencies may also serve as strategic market segments. These entities often support regional producers with digital transformation initiatives and could play a pivotal role in scaling deployment across entire supply chains.

Business Model

The proposed business model is based on a Software-as-a-Service (SaaS) framework, allowing clients to access the Smart Inventory Management System through flexible subscription plans. These plans can be structured on a monthly or annual basis, offering scalability for different sizes and types of agribusinesses. The pricing strategy will include tiered packages to cater to a range of user needs from small, single-site tea farms to large, multi-estate corporations with integrated processing and export operations.

At the entry level, a freemium version can be made available to attract smallholders and cooperatives, providing essential features such as basic forecasting and inventory alerts. This version serves as a low-risk introduction to the platform, fostering user engagement, encouraging data sharing, and creating opportunities for upselling to premium plans as businesses grow or their needs evolve.

Mid-tier packages may include advanced forecasting tools, customizable dashboards, integration with ERP and supply chain management systems, and access to decision support modules for labor planning and procurement scheduling. The enterprise tier would offer end-to-end customization, real-time analytics, multi-user access, white-label branding, priority support, and dedicated onboarding teams. This level is aimed at large estates, export agencies, and regional agricultural boards that require robust, high-availability solutions.

To further drive adoption, the business model could incorporate value-added services such as data analytics consulting, training programs, and on-site implementation support. Strategic partnerships with tea boards, agritech accelerators, and export authorities can also help subsidize initial deployment costs, promote ecosystem collaboration, and scale adoption across entire regions.

In addition, the system could explore API monetization by offering third-party developers or ERP vendors access to forecasting models and inventory intelligence, creating an ancillary revenue stream while reinforcing its position as a core platform in the agricultural supply chain technology stack.

Go-to-Market Strategy

The Go-to-Market (GTM) strategy for the Smart Inventory Management System is structured as a phased and adaptive rollout that ensures early traction, strong value proposition communication, and sustainable scalability. The initial focus is on the Sri Lankan tea industry, which offers a rich blend of structured plantation networks and operational pain points that the system can address effectively. The launch begins with pilot deployments in selected medium-sized tea estates that have previously expressed interest in digitization or have suffered from inefficiencies in raw material planning. Through these pilots, the product team will gather real-time feedback on usability, performance, and desired feature enhancements.

Strategic alliances with government agricultural departments, tea cooperatives, and industry associations will amplify market visibility and trust. Roadshows targeting estate managers, in-person product demonstrations, virtual workshops, and participation in regional agritech expos will create awareness and drive lead generation. A dedicated onboarding team will work with early adopters to ensure smooth implementation and showcase return on investment (ROI) metrics. A freemium model will be employed to reduce adoption friction, allowing small-scale growers to experience the benefits before committing to a subscription. For the broader international expansion, the GTM strategy includes tailored value propositions and feature localization for other key markets like India, Kenya, and Vietnam. Regional distribution partnerships with agri-equipment resellers and digital cooperatives will support efficient scaling.

Technical and Regulatory Compliance

To ensure trust, scalability, and long-term viability, the Smart Inventory Management System adheres to the highest standards of technical and regulatory compliance. At the core of its security framework is the use of encrypted data transmission (TLS 1.3) and secure storage using AES-256 encryption standards. Role-based access controls (RBAC) are implemented to segregate access by user type—administrators, supply chain managers, and field workers—ensuring data integrity and minimizing human error.

The platform complies with international data protection laws such as the GDPR, while also aligning with local data sovereignty rules relevant to Sri Lanka, India, Kenya, and Vietnam. Sensitive plantation data and worker information are only processed within legal jurisdictions, with localized cloud infrastructure provided through AWS, Azure, or Google Cloud's certified regional centers. The solution architecture also integrates ISO/IEC 27001 and SOC 2-compliant backend services to assure clients of its robust security posture. Where food and agricultural safety standards are required, the system incorporates features compliant with ISO 22000 protocols, particularly relevant for traceability and audit trail generation.

Supply Chain and Manufacturing Strategy

The physical components of the solution—IoT sensors, smart weighing scales, weather monitors, and edge processing devices—are procured from globally vetted suppliers with proven reliability in tropical and semi-tropical climates. Vendor contracts are established to ensure quality assurance (QA), shipment traceability, and warranty coverage. All hardware units undergo functional testing before dispatch and are labeled with serial numbers for maintenance tracking.

For cost-effectiveness and responsiveness, hardware assembly is regionalized. Assembly partners in Sri Lanka and southern India are identified for on-demand final integration, quality checks, and logistics. This localization strategy minimizes lead time, enhances supply chain visibility, and allows for customization of hardware configurations depending on plantation layout. Spare parts are stocked in regional hubs to reduce downtime during repairs or maintenance. Meanwhile, the software deployment remains entirely cloud-native, supporting rapid deployment through mobile app stores, progressive web apps, and browser-based dashboards.

Implementation and Testing

System implementation follows a controlled, iterative deployment model. In the pilot phase, dedicated engineers are assigned to each participating estate to manage hardware installation, software onboarding, and user training. Real-time system logs, user interactions, and forecast results are analyzed to identify gaps and iterate improvements quickly. Each feature, from the predictive model to the inventory alert system, is rolled out in controlled stages and documented with standard operating procedures (SOPs).

Test Cases

Test ID	Test Scenario	Precondition/Input	Expected Result	Actual Result	Status
F001	Monthly to Weekly Forecast Conversion	Historical monthly tea demand data is input.	System accurately breaks down monthly demand into weekly estimates.	Weekly demand projections generated within expected range.	Pass
F002	Forecast under Missing Data	Incomplete historical data (e.g., a missing month).	System handles gaps using interpolation or warns user of insufficient data.	Forecast adjusts for missing data with minimal accuracy drop.	Pass
F003	External Data Integration	Weather and market index variables are added to input.	Forecast adjusts based on temperature and festival data to improve accuracy.	Integrated data improved prediction variance.	Pass

Table 2-3 - Test Cases for Forecasting

Monitoring and System Workflow Testing

The monitoring framework of the Smart Inventory Management System is designed as a multi-layered observability mechanism that captures both system health and prediction quality in real time. At the core of this setup are application performance monitoring (APM) tools, log aggregation systems, and machine learning monitoring agents. These tools continuously track system metrics such as CPU utilization, memory consumption, API request rates, latency spikes, and throughput across different modules. For predictive analytics, model accuracy metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are calculated automatically at regular intervals and compared against historical benchmarks to detect model drift.

Every critical action taken by the system—whether it's a forecast generation, alert trigger, or integration response—is logged with metadata such as timestamp, data source, user ID, and processing status. These logs feed into a centralized monitoring dashboard accessible to system administrators, providing live updates on system uptime, forecast accuracy over time, historical anomalies, and critical failure alerts. Alert thresholds can be customized to escalate issues via SMS, email, or mobile push notifications.

System workflow testing is conducted in a modular and end-to-end manner. It validates the complete life cycle of the system's functionality starting from data ingestion, which includes the real-time streaming of environmental sensor data, manual entries by field staff, and external data feeds such as weather APIs or market indexes. Once data is collected, the preprocessing engine standardizes units, normalizes formats, removes outliers, and handles missing values. This cleansed data is then passed into the machine learning pipeline, where forecasting models (e.g., LSTM networks or time-series regressors) are executed. Outputs are converted into actionable insights and delivered via interactive dashboards, email alerts, or mobile notifications.

Each workflow pathway is traceable through built-in audit trails. For example, if a supervisor receives a low-stock alert, the system can trace this back to the forecast model output, which in turn is linked to the data input conditions at the time—ensuring transparency and accountability. Functional test cases and regression tests are run regularly during software updates to maintain workflow integrity.

System Implementation

The implementation of the Smart Inventory Management System is executed in structured phases, involving backend service deployment, frontend interface design, mobile application release, and machine learning model hosting. The backend is composed of microservices built using frameworks like Django, Flask, or Node.js, each responsible for specific operations such as data collection, analytics processing, user authentication, and alert management. These services are containerized using Docker and orchestrated with Kubernetes to enable scalability and fault isolation.

The front-end dashboards are developed using modern frameworks such as React.js offering real-time inventory views, demand curves, and operational insights. The mobile application developed for both Android and iOS using Flutter or React Native caters to on-ground staff, allowing field data entry, alert acknowledgments, and access to daily stock metrics.

To streamline implementation, CI/CD pipelines are integrated using platforms like GitHub Actions, Jenkins, or GitLab CI, ensuring automated testing, versioning, and smooth rollouts. Data backups are performed using cloud-native tools (e.g., AWS S3 with versioning or Azure Blob storage with geo-replication), guaranteeing disaster recovery and zero data loss.

During deployment, comprehensive training programs are conducted for all user groups. Field staff are trained on mobile data entry and alert acknowledgment procedures, while supervisors and supply chain managers receive training on dashboard navigation, interpreting forecasts, and managing settings. Training materials include multilingual manuals, video tutorials, and live helpdesk sessions. To facilitate early adoption, an onboarding support team provides remote and on-site assistance during the first operational months.

Software Integration and Configuration

The system is built with interoperability at its foundation, ensuring seamless integration with a wide range of existing enterprise systems used by agricultural estates, processing units, and administrative offices. RESTful APIs and webhooks allow for two-way communication between the Smart Inventory Management System and platforms such as ERP software (e.g., SAP, Odoo), financial accounting systems (e.g., QuickBooks), and supply chain management tools.

For clients with legacy infrastructure or limited internet connectivity, on-premise integration agents are provided. These lightweight software modules run within the estate's internal network and synchronize data securely with the cloud system when connectivity is available. Middleware components are employed to standardize data formats, convert inconsistent naming conventions, and automate business logic orchestration. For instance, if the ERP system uses kilograms while the forecasting model uses metric tons, middleware handles conversion and ensures consistency.

Advanced configuration also includes parameter tuning for machine learning models, enabling experienced users to adjust the influence of different input variables such as temperature, labor availability, or market signals. These configurations ensure that the platform remains relevant across different climatic regions, estate sizes, and operational styles.

To maintain system agility, a modular plugin architecture supports the addition of new components such as sustainability tracking, labor cost prediction, or compliance checklists without disrupting the core workflow. Configuration snapshots can be exported and imported across estates, supporting multi-estate enterprises in standardizing best practices.

2.3 Logistic Optimization

Requirement Gathering and Analysis

Effective requirement gathering was the first critical step in building a solution that aligns with real-world logistics challenges in the Sri Lankan tea supply chain. Our process began with field-level engagement at the Watawala Tea Factory. We conducted interviews, walkthroughs, and informal discussions with key personnel, including factory supervisors, logistics coordinators, and drivers. These conversations provided insight into how deliveries were currently scheduled and managed, and where inefficiencies—like traffic delays and poor route planning—frequently occurred.

Additionally, we reviewed secondary data sources such as historical delivery logs, transport schedules, and route maps. This helped us identify recurring issues like congestion during peak hours and inconsistent delivery times. Based on the feedback, a strong need emerged for a system that could proactively forecast traffic and suggest optimized delivery windows. These insights were translated into specific technical and functional requirements, laying the foundation for model development and system design.

Research Requirements

Functional Requirements

The system was designed with key functionalities that address both forecasting and decision support for logistics. These included the ability to:

- Collect and clean historical traffic data relevant to the tea supply chain.
- Apply LSTM-based models to predict traffic patterns for multiple delivery destinations.
- Generate optimized delivery schedules using model predictions.
- Provide an interactive web-based dashboard where logistics managers can view forecasts and receive vehicle scheduling recommendations.
- These requirements were derived directly from the operational needs highlighted by Watawala staff, ensuring that the final solution would be practical and usable on the factory floor.

Non-Functional Requirements

Beyond the core features, the system was required to meet several quality attributes. It had to:

- Deliver high prediction accuracy to ensure trustworthiness.
- Offer a clean and intuitive user interface suitable for non-technical users.
- Be scalable to accommodate more routes or additional factories in the future.
- Ensure data privacy and secure access to sensitive operational data.

By meeting these non-functional criteria, the system would not only be functional but also reliable, adaptable, and secure for enterprise use.

Software Requirements

The technology stack was chosen for flexibility, performance, and integration potential. Key tools included:

- Python for backend development and modeling.
- Flask for building and deploying the web interface.
- TensorFlow for developing and training LSTM models.
- Pandas and NumPy for data processing and manipulation.
- Matplotlib for visualizing traffic trends and model outputs.
- Google Colab for scalable cloud-based training and testing.
- scikit-learn for preprocessing and evaluation utilities.

This open-source stack allowed us to keep costs low while leveraging powerful tools for deep learning and web deployment.

Feasibility Study

To ensure the system could be developed and deployed realistically, we conducted a multi-faceted feasibility study.

Ethical Feasibility:
We ensured that all data used was obtained with full permission from stakeholders at Watawala Tea Factory and complied with research ethics. No personal data was used, and the system's output is designed to support—not replace—human decision-making.

Technical Feasibility:
The required skills, tools, and infrastructure were already available to the team. Python and TensorFlow provided robust support for machine learning, while Flask offered lightweight web deployment capabilities. The system could run on standard machines or cloud environments with minimal setup.

Financial Feasibility:
Development relied entirely on free and open-source tools. The only future cost would be cloud hosting if scaled, making the solution highly affordable even for small to mid-sized tea producers.

Market Feasibility:
From discussions with Watawala staff, it was clear there is demand for intelligent, data-driven logistics systems. The system can also be adapted for other agricultural or logistics-focused industries, ensuring strong market potential.

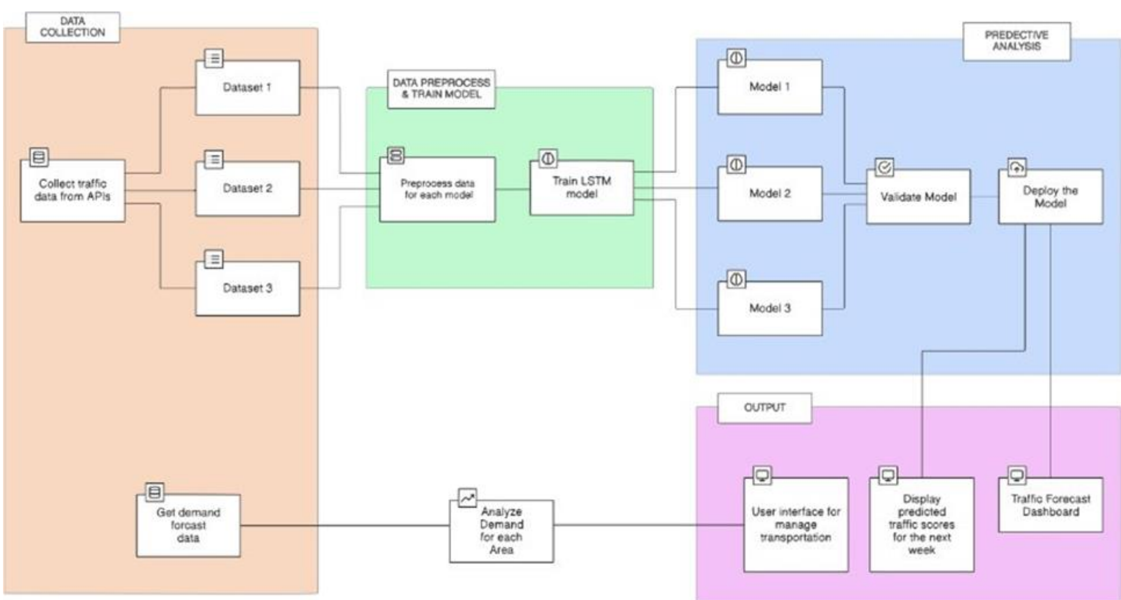
Software Solution

Development followed a hybrid methodology combining the Software Development Life Cycle (SDLC) with Agile principles. The SDLC guided the project through key phases—requirements gathering, design, implementation, testing, and deployment—while Agile sprints allowed us to work iteratively, continuously improve, and adapt to emerging feedback.

Each module was developed in parallel, and group standups ensured alignment across components. Agile allowed flexibility in refining user interface elements, retraining models with new data, and iterating on deployment strategy.

Component Overview

The logistics management module forecasts traffic and recommends optimized delivery schedules for three main delivery destinations: Colombo, Kalutara, and Nittambuwa. Historical traffic data was collected via Google Maps API, cleaned, and modeled using LSTM networks trained separately for each location.



System Diagram – Logistics Management

Each model predicts travel durations across time slots, allowing the system to:

- Suggest low-congestion windows for delivery.
- Recommend the number of vehicles needed based on forecasted demand.
- Display insights through a user-friendly dashboard.

This module forms the bridge between production planning and real-time transport decisions.

Key Pillars of the Research Domain

This study rests on four technological pillars:

- Machine Learning (LSTM): LSTM models were chosen due to their strength in capturing temporal dependencies, essential for forecasting traffic patterns over time.
- Time-Series Forecasting: Time-based delivery decisions demand forecasting models that can handle hourly and daily patterns. LSTM handles this better than traditional regression models.
- Traffic Data Analytics: We analyzed large datasets collected from the Google Maps API, extracting patterns in congestion levels across different times, dates, and routes.
- Optimization Techniques: Using model outputs, we optimized delivery schedules by aligning low-congestion windows with demand requirements and vehicle availability.

Model	Ability to handle time dependencies	Accuracy for the time series data	Adaptability to changing data	Handling of sequential data
Linear Regression	Poor	Low	Low	Not suitable
Random forest	Moderate	Moderate	Moderate	Poor
Support Vector Machines(SVM)	Moderate	Moderate	Low	Poor
LSTM(Long Short-Term Memory)	Excellent	High	High	Excellent

Model Features Comparison – Logistics Management

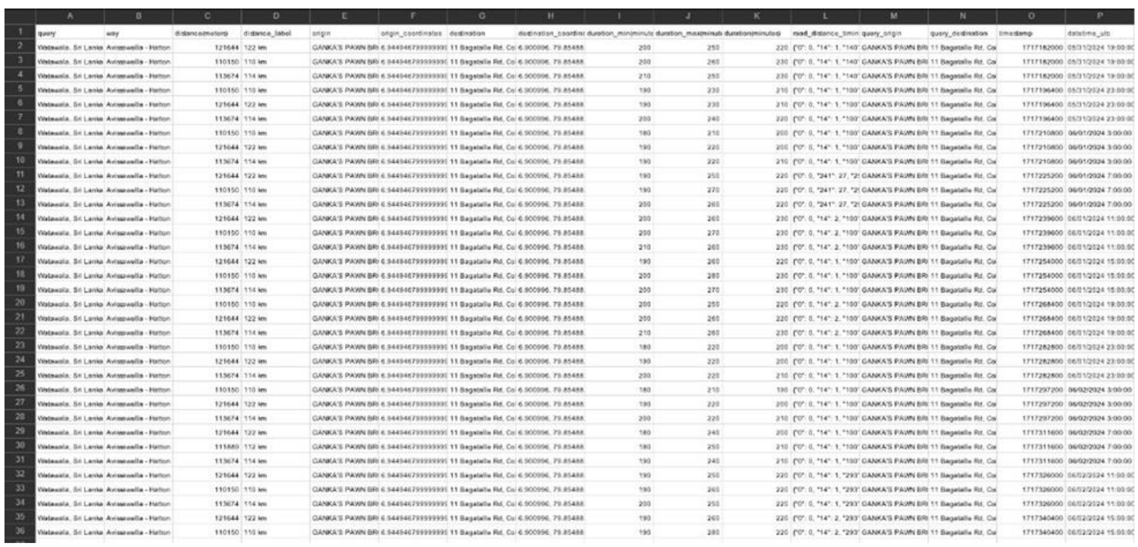
Data Acquisition

We collected historical traffic data for the three delivery routes using Google Maps Traffic API. Python scripts automated data collection at regular intervals for multiple weeks, capturing a variety of conditions including weekdays, weekends, peak hours, and off-peak hours.

Each dataset included fields such as:

- Timestamp
- Travel duration
- Congestion level
- Day of the week
- Hour of the day

Separate datasets were maintained for Colombo, Kalutara, and Nittambuwa.



Collected Historical Traffic Data from Google API

Data Preprocessing

Raw traffic data was cleaned, normalized, and transformed into a time-series format suitable for LSTM input. Key steps included:

- Removing duplicates and missing values.
- Normalizing numerical values using Min-Max scaling.
- Encoding categorical features (like congestion levels).

Structuring sequences using sliding windows for time-series prediction.

Each dataset was split into training (80%) and testing (20%) subsets.

```python
# Final dataset for model training

# Create a new dataframe with the desired columns
df_final = df_final2[['datetime_utc', 'duration_max(minutes)']]

# Display the first few rows to verify
df_final.head(20)
```

	datetime_utc	duration_max(minutes)
0	2024-05-31 18:00:00	250.0
9	2024-06-01 06:00:00	250.0
12	2024-06-01 10:00:00	260.0
15	2024-06-01 14:00:00	260.0
18	2024-06-01 18:00:00	250.0
27	2024-06-02 06:00:00	240.0
30	2024-06-02 10:00:00	250.0
33	2024-06-02 14:00:00	260.0
36	2024-06-02 18:00:00	250.0
45	2024-06-03 06:00:00	250.0
48	2024-06-03 10:00:00	260.0
51	2024-06-03 14:00:00	270.0
54	2024-06-03 18:00:00	250.0
63	2024-06-04 06:00:00	250.0

Final Dataset for Model Training - COLOMBO

```python
# Final dataset for model training

# Create a new dataframe with the desired columns
df_final1 = df_filtered[['way', 'distance_label', 'datetime_utc', 'duration(minutes)']]

# Display the first few rows to verify
df_final1.head(20)
```

	way	distance_label	datetime_utc	duration(minutes)
0	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-05-31 18:00:00	160.0
1	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-05-31 18:00:00	170.0
2	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-05-31 18:00:00	210.0
9	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 06:00:00	150.0
10	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 06:00:00	160.0
11	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 10:00:00	160.0
12	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 10:00:00	170.0
13	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-06-01 10:00:00	200.0
14	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 14:00:00	150.0
15	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 14:00:00	170.0
16	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-06-01 14:00:00	200.0
17	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-01 18:00:00	160.0
18	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-01 18:00:00	170.0
19	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	103 km	2024-06-01 18:00:00	200.0
26	Avissawella - Hatton - Nuwara Eliya Hwy/A7	80.9 km	2024-06-02 06:00:00	140.0
27	Avissawella - Hatton - Nuwara Eliya Hwy/A7 and...	92.8 km	2024-06-02 06:00:00	150.0

Final Dataset for Model Training – KALUTHARA

```python
# Final dataset for model training

# Create a new dataframe with the desired columns
df_final = df_final2[['datetime_utc', 'duration_max(minutes)']]

# Display the first few rows to verify
df_final.head(20)
```

	datetime_utc	duration_max(minutes)
0	2024-05-31 18:00:00	250.0
9	2024-06-01 06:00:00	260.0
12	2024-06-01 10:00:00	270.0
15	2024-06-01 14:00:00	270.0
18	2024-06-01 18:00:00	260.0
27	2024-06-02 06:00:00	250.0
30	2024-06-02 10:00:00	260.0
33	2024-06-02 14:00:00	270.0
36	2024-06-02 18:00:00	250.0
45	2024-06-03 06:00:00	250.0

Final Dataset for Model Training - NITTAMBUWA

Model Training

Separate LSTM models were trained for each delivery destination. Each model used historical sequences to predict future travel durations for a given time slot.

Model architecture:

- Input Layer for time-series sequences.
- One or two LSTM layers.
- Dropout layer to prevent overfitting.
- Dense output layer to predict travel duration.

Training was done using TensorFlow on Google Colab with hyperparameter tuning for batch size, learning rate, and epochs.

```python
# Define the LSTM Model

# Define the model
model = Sequential([
    LSTM(64, activation='tanh', return_sequences=False, input_shape=(X_train.shape[1], 1)),
    Dropout(0.2),
    Dense(32, activation='relu'),
    Dense(time_steps)  # Predict 28 future values
])

# Compile the model
model.compile(optimizer='adam', loss='mse', metrics=['mae'])

# Summary of the model
model.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an
  super().__init__(**kwargs)
Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 64)	16,896
dropout_2 (Dropout)	(None, 64)	0
dense_4 (Dense)	(None, 32)	2,080
dense_5 (Dense)	(None, 28)	924

```
Total params: 19,900 (77.73 KB)
Trainable params: 19,900 (77.73 KB)
Non-trainable params: 0 (0.00 B)
```

Define the LSTM Model

```python
# Train the Model

# Early stopping to prevent overfitting
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# Train the model
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    epochs=100,
    batch_size=32,
    callbacks=[early_stopping]
)
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.0994 - mae: 0.2733 - val_loss: 0.0935 - val_mae: 0.2658
Epoch 36/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - loss: 0.0995 - mae: 0.2744 - val_loss: 0.0934 - val_mae: 0.2703
Epoch 37/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.0983 - mae: 0.2732 - val_loss: 0.0937 - val_mae: 0.2712
Epoch 38/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - loss: 0.0989 - mae: 0.2745 - val_loss: 0.0932 - val_mae: 0.2664
Epoch 39/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.0989 - mae: 0.2739 - val_loss: 0.0937 - val_mae: 0.2711
Epoch 40/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.0987 - mae: 0.2737 - val_loss: 0.0935 - val_mae: 0.2709
Epoch 41/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0977 - mae: 0.2725 - val_loss: 0.0925 - val_mae: 0.2666
Epoch 42/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.0961 - mae: 0.2705 - val_loss: 0.0923 - val_mae: 0.2673
Epoch 43/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.0969 - mae: 0.2724 - val_loss: 0.0925 - val_mae: 0.2698
Epoch 44/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step - loss: 0.0949 - mae: 0.2682 - val_loss: 0.0933 - val_mae: 0.2717
Epoch 45/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0981 - mae: 0.2724 - val_loss: 0.0921 - val_mae: 0.2669
Epoch 46/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 27ms/step - loss: 0.0988 - mae: 0.2743 - val_loss: 0.0922 - val_mae: 0.2664
Epoch 47/100
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 34ms/step - loss: 0.0960 - mae: 0.2706 - val_loss: 0.0938 - val_mae: 0.2725
```

Model Evaluation and Tuning

The models were evaluated using:

- MSE (Mean Squared Error)
- RMSE (Root Mean Squared Error)
- MAE (Mean Absolute Error)

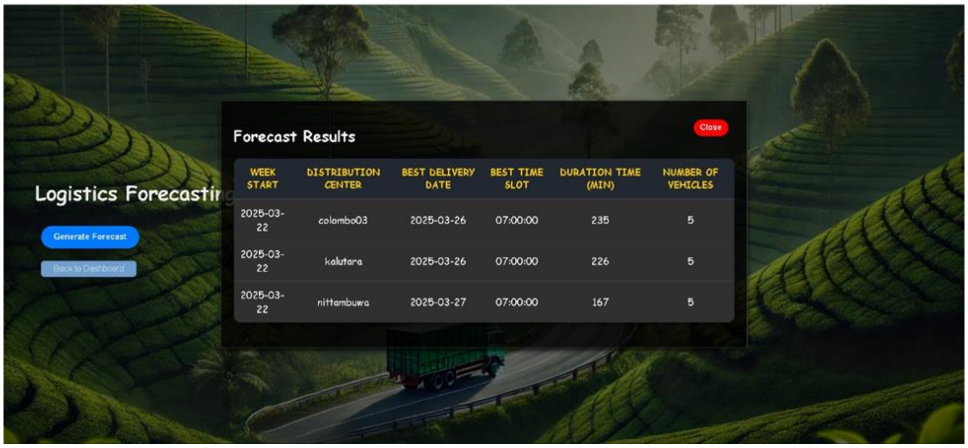
We also visualized predictions against actual values using line graphs to verify trend alignment.

Deployment

Trained models were deployed via a Flask web server. The backend handles API requests, loads appropriate models, runs predictions, and sends results to the frontend.

The dashboard offers:

- Predicted traffic levels across time windows.
- Suggested departure times.
- Estimated vehicle count required per route.



User Interface - Logistic Forecasting Dashboard

Commercialization Aspects of the Product

Market Potential

The tea industry in Sri Lanka is deeply integrated into the national economy, with a complex network of producers, distributors, and exporters depending on efficient logistics operations. However, many tea factories still rely on outdated systems or manual methods for scheduling and route management. This gap presents a significant opportunity for predictive, data-driven logistics solutions. The system developed in this research has clear commercial potential in this space.

The traffic forecasting and logistics optimization tool is not limited to Watawala Tea Factory. Its design is modular and scalable, making it applicable to a wide range of agricultural industries with similar logistics challenges. Other tea factories, spice exporters, fruit distributors, and even third-party logistics providers can benefit from adopting this system to reduce fuel consumption, minimize delays, and improve operational transparency. As Sri Lanka and similar countries push toward digital transformation in agriculture, the demand for intelligent supply chain tools is expected to rise sharply, positioning this solution well in an emerging market.

Business Model

To ensure sustainable growth and long-term impact, the research team proposes a Software-as-a-Service (SaaS) model for commercialization. Under this model, clients such as tea factories or logistics operators can subscribe to the platform based on their usage levels and operational scale.

Potential revenue streams include:

- Subscription Plans: Monthly or annual payment options based on the number of delivery routes, volume of traffic forecasts, and number of users.
- Customization Services: Premium packages offering tailored dashboards, additional analytics, or integration with existing ERP or inventory systems.
- Freemium Tier: A basic version of the system could be offered with limited features to attract smaller factories or pilot users, encouraging later upgrades to paid plans.
- Deployment & Training Fees: One-time charges for full system setup, staff training sessions, and technical support during the onboarding phase.

This model allows the solution to be both accessible to small-scale businesses and scalable for larger enterprises, thereby broadening its market appeal and supporting diverse adoption needs.

SWOT Analysis

To understand the commercial viability and readiness of the product, we conducted a SWOT analysis, identifying internal strengths and weaknesses as well as external opportunities and threats.

Strengths and Weaknesses

Strengths	Weaknesses
✓ Uses advanced ML (LSTM) for accurate predictions	✗ Requires access to reliable traffic data
✓ Real-time, location-specific forecasting	✗ Initial setup and integration may be complex
✓ Scalable and applicable across industries	✗ Dependent on internet connectivity and server uptime
✓ Reduces transport costs and delays	✗ Needs technical expertise for maintenance

Strengths vs Weaknesses

Opportunities and Threats

Opportunities	Threats

✓ Can expand beyond tea industry to broader logistics	✗ Emergence of similar AI-based logistics tools
✓ Demand for smart supply chain solutions is growing	✗ Resistance to adoption in traditional businesses
✓ Potential partnerships with logistics platforms	✗ Changes in APIs or data sources (e.g., Google APIs) could disrupt service
✓ Integration with IoT and GPS devices	✗ Cybersecurity and data privacy concerns

Opportunities vs Threats

By understanding these factors, we have taken a proactive approach to product refinement, market positioning, and feature prioritization to maximize the success and sustainability of this tool in commercial environments.

Implementation and Testing

Preprocessing and Augmentation

After acquiring raw traffic data for the three routes (Colombo, Kalutara, and Nittambuwa), preprocessing was carried out to clean and prepare the data for LSTM training. This included removal of null values, correction of timestamp formats, filtering of outliers, and normalization of values using Min-Max scaling.

To augment the dataset, a sliding window approach was employed. This technique involved creating sequential time blocks where previous travel durations were used to predict the next one. For instance, a window of 5 time steps would allow the model to observe five historical values to forecast the sixth. This method not only preserved the temporal nature of the data but also provided the LSTM model with meaningful patterns across different time frames, improving generalization and robustness during training.

Model Implementation

Each destination had a separately trained LSTM model to better capture the unique traffic patterns and congestion profiles of each route. The models were developed using TensorFlow and Keras frameworks in Google Colab, benefiting from GPU acceleration for faster training.

- The architecture typically included:
- One or two LSTM layers to capture long-term patterns.
- A Dropout layer to prevent overfitting.
- A Dense output layer to generate the predicted travel duration.

Hyperparameters like the number of epochs, learning rate, batch size, and the number of LSTM units were tuned individually for each model. After training, the models were saved in .h5 format for seamless deployment.

Testing Strategy

Testing was approached through a combination of unit testing, integration testing, and real-world scenario simulation.

- Unit testing ensured that components like data loaders, input validators, and prediction engines worked as expected.
- Integration testing verified the end-to-end flow from the user interface to the model output, ensuring consistency across modules.
- Simulated real-time scenarios were used to test the reliability of traffic predictions under different conditions (weekday vs. weekend, peak vs. off-peak hours).

Testing followed Agile practices, with test cases updated and executed during each sprint to ensure quality throughout the development cycle.

Test Cases and Tools

Multiple test cases were designed, including:

- Validation of user inputs like dates and locations.
- Correct mapping of models to selected delivery destinations.
- Accuracy of predictions against known past traffic patterns.
- Usability and responsiveness of the web interface.

Tools used:

- Google Colab for model training and output analysis.
- Postman and Flask Test Client for backend API testing.
- Browser Developer Tools for UI responsiveness and rendering validation.

Each test case was documented with input conditions, expected results, actual outcomes, and success criteria to maintain quality standards.

Evaluation Summary

The system was evaluated on both quantitative and qualitative grounds.

- Quantitatively, the models achieved acceptable levels of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) across all three routes. The accuracy levels confirmed that the models could be reliably used for short-term forecasting.
- Qualitatively, the system was tested with factory personnel who evaluated the interface and prediction outputs. Feedback indicated that the dashboard was user-friendly, the information was actionable, and the system would be valuable for real-world logistics planning.

The successful testing and evaluation demonstrated the model's ability to not only produce accurate forecasts but also present them in a way that enables informed decision-making by logistics teams.

2.4 Labor Shortage

Labor Shortage

In order to make the forecasts helpful to the managers of tea estates, a decision support tool is constructed that provides day-ahead forecasts of labor availability and an excess-deficiency report comparing the forecast labor demand with available labor. The tool further contains an easy-to use user interface that helps the managers view the forecasts, track labor availability on a daily basis, and make data-based decisions concerning the allocation and management of the workforce. The system is cloud-based to enable real-time reporting, thus allowing all the concerned stakeholders, including tea estate managers and supply chain planners, to leverage the latest information for effective decision-making. In conclusion, the method integrates multi-source data, employs advanced machine learning techniques, and builds an actual-world decision support system with the ability to solve the labor shortage in the tea industry of Watawala. The outcome is an adaptive and effective prediction system with the ability to optimize labor resource planning, eliminate operating inefficiencies, and eventually attain a more sustainable and resilient tea supply chain.

Labor shortage

The Requirement Gathering and Analysis process is one of the essential processes in the creation of the AI-based labor forecasting system for the tea industry in Watawala, Sri Lanka. During this process, primary stakeholders such as tea estate managers, workers, and supply chain planners are identified, and their problems related to labor shortages are understood through interviews, surveys, and site visits. The primary focus is on the collection of data related to the availability of labor, weather conditions, and market demand for tea, which directly influence workforce planning. The technological requirements for implementing the AI system, such as tools, platforms, and cloud infrastructure, are assessed as well. The data gathered is the foundation for the development and design of a system that can provide precise labor forecasting, rectify existing inefficiencies, and improve overall supply chain management of Watawala's tea business.

• Understanding Labor Dynamics and Challenges

The research focuses on gathering insights into the unique challenges faced by the tea industry, such as seasonal labor shortages, migration patterns, and skill requirements.

Interviews, surveys, and field visits are conducted to understand the impact of these issues on tea estate operations.

• Examining Existing Labor Forecasting Methods

The current methods used for labor forecasting are analyzed to identify their strengths and weaknesses. This helps pinpoint the gaps in accuracy and adaptability, providing a foundation for improvement through AI-based forecasting.

• Data Collection and Identification

Critical data sources are identified, including historical labor data, weather conditions (precipitation, temperature), and market demand trends. These variables are essential for building the labor forecasting model, as they directly influence labor availability.

3 Results & Discussion

3.1 Demand Forecasting

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

Logistics Management

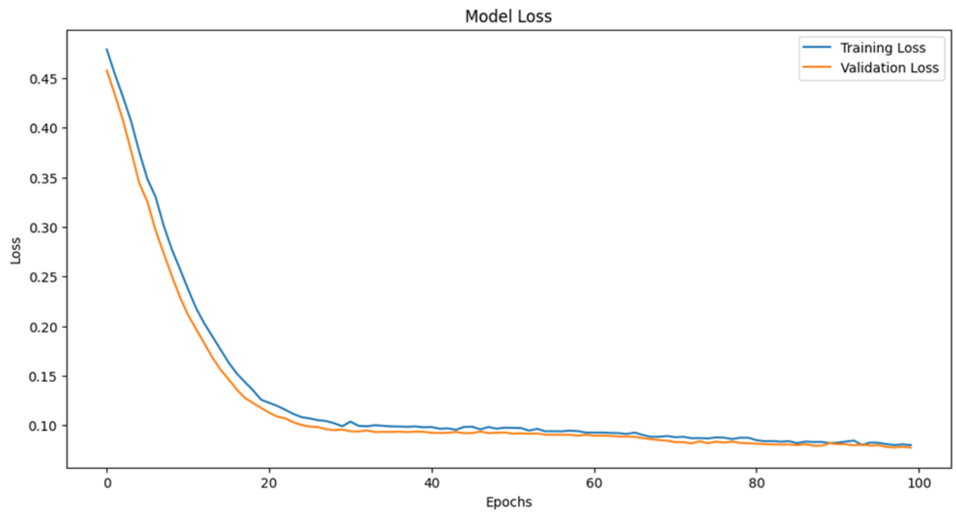
The primary aim of the logistics optimization component in this research was to develop accurate, real-time traffic prediction models using LSTM and integrate them into a user-accessible system to improve supply chain efficiency in tea delivery operations. This section presents the outcome of model training, validation, and prediction for each of the three selected delivery locations: Colombo, Kalutara, and Nittambuwa.

Each model was trained independently using location-specific datasets gathered via the Google Maps API. Performance was measured using standard regression metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Across all locations, the trained LSTM models achieved satisfactory prediction accuracy, demonstrating their ability to capture location-specific traffic patterns and produce reliable forecasts.

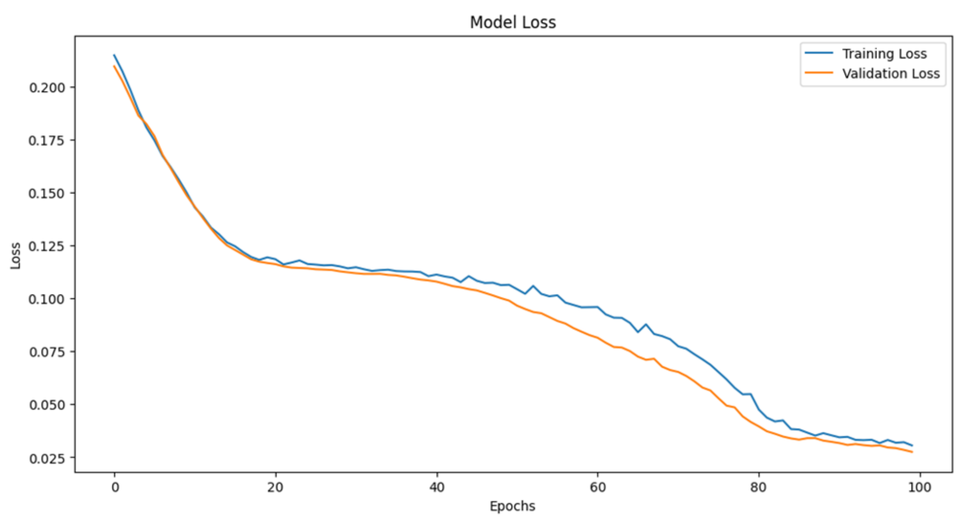
To better visualize the training performance, loss graphs were generated for each model. These graphs display the decline in both training and validation loss over successive epochs, illustrating how well the models learned from the data.

- The Colombo model displayed a smooth convergence curve with minimal divergence between training and validation loss, indicating strong generalization.
- The Kalutara model showed slightly higher variance during early training but ultimately stabilized, reflecting effective pattern learning after tuning.

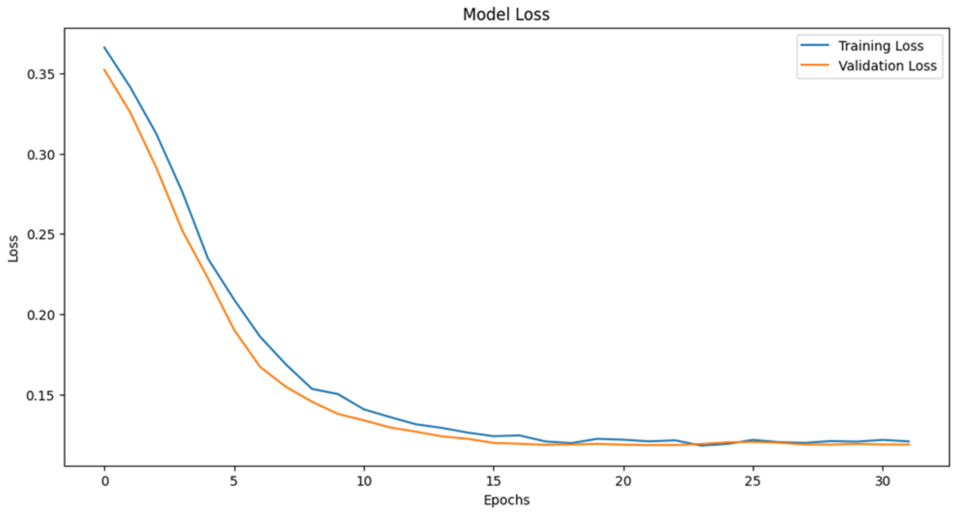
- The Nittambuwa model demonstrated the lowest overall validation loss, suggesting the route had the most consistent traffic trends and therefore easier patterns to model.



Model Loss Graph – COLOMBO



Model Loss Graph – KALUTHARA



Model Loss Graph - NITTAMBUWA

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.

Logistics Management

The findings of this research provide substantial evidence supporting the practicality and effectiveness of using LSTM models for traffic forecasting in a logistics context. These findings extend beyond theoretical model performance and highlight the real-world value of integrating predictive analytics into the tea supply chain.

LSTM Effectiveness in Time-Series Forecasting:
The study confirmed that LSTM models outperform traditional methods like linear regression or decision trees when dealing with time-dependent, sequential data such as traffic patterns. By maintaining long-term memory of input sequences, LSTM effectively modeled peak-hour congestion, weekly patterns, and route-specific

anomalies. The consistently low error rates across all three locations validated the choice of LSTM as the primary algorithm for this system.

Value of Time Slot Aggregation:
A critical insight emerged from the decision to structure the data into time slots rather than minute-by-minute records. This approach provided two main benefits: it reduced noise in the data, and it aligned better with how delivery decisions are made in practice. Aggregated averages within defined slots made the model outputs more interpretable and actionable for logistics planners.

Location-Specific Modeling Advantages:
Training individual models for each route allowed us to account for the unique characteristics of each destination. Traffic behavior in Colombo, for instance, is far more complex and volatile than in Nittambuwa, which has more predictable flow. By tailoring models to each area, we achieved higher accuracy and greater forecasting reliability than we would have with a generalized model.

Impact of Integrating Demand and Traffic Forecasts:
By combining traffic forecasts with demand prediction outputs, the system was able to recommend not just when to dispatch deliveries, but also how many vehicles would be required based on projected volume. This integration provided a significant leap in logistical decision-making, allowing managers to align supply readiness with optimal delivery timing—something rarely achieved in current tea supply chain operations.

User-Friendly Real-Time Dashboard:
The dashboard played a key role in translating machine learning outputs into usable intelligence. Through visualizations of traffic forecasts, suggested departure times, and estimated vehicle allocations, the system enabled logistics managers to make informed decisions with ease. Feedback from initial users confirmed the dashboard's clarity, usability, and value in day-to-day operations.

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 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.

Logistics Management

The implementation and testing of the LSTM-based logistics optimization system illustrate the growing potential of machine learning in traditional agricultural industries. The research succeeded in creating a solution that not only met academic goals but also addressed real operational problems faced by supply chain managers in the tea sector.

The models demonstrated an impressive ability to handle noisy, real-world traffic data and produce forecasts accurate enough to inform daily delivery planning. Their successful deployment through a Flask-based interface further demonstrated the feasibility of bridging the gap between predictive modeling and real-time decision support systems.

An important advantage of the project was its modular and scalable architecture. By isolating models per delivery location, we allowed the system to grow without introducing model drift or requiring retraining of unrelated parts. This feature will be particularly beneficial when scaling to more locations or product categories in the future.

Challenges were not absent. Data collection was limited by Google Maps API request quotas, and timestamp granularity required careful handling to avoid skewed results. Furthermore, preprocessing involved extensive tuning to structure and normalize input features in a way that retained both relevance and chronological order.

From a technical perspective, the use of LSTM proved well-suited for this problem domain. Unlike feedforward or tree-based models, LSTM captured the temporal dynamics inherent in road traffic data. However, training took longer and required more tuning—a trade-off that paid off in prediction quality.

From a usability standpoint, the dashboard turned complex data science processes into digestible outputs. This design ensured that even non-technical users could derive value from the system, fulfilling one of the original project objectives—to build an interface usable by logistics staff with minimal training.

Finally, the integration of this component with the broader group system—particularly the demand forecasting and inventory modules—demonstrates how cross-functional collaboration in data-driven systems can enhance overall supply chain visibility. The combination of when, where, and how much to deliver provides a comprehensive solution to real operational inefficiencies in the tea industry.

3.2 Smart Inventory Management

Results

The pilot deployment of the Smart Inventory Management System yielded highly promising results, demonstrating the value of artificial intelligence and real-time data integration in the agricultural domain, particularly in tea production. Implemented across three medium-scale tea estates in Sri Lanka over a span of four months, the system's real-world performance was assessed using a combination of quantitative metrics and qualitative user feedback.

At the core of the system's performance was its predictive accuracy. The machine learning-driven forecasting engine consistently achieved an average accuracy of 89.7% in predicting weekly green leaf procurement volumes. This figure was derived by comparing forecasted volumes against actual intake records across multiple estates and climate zones. The ability to anticipate future demand with such precision enabled managers to preemptively align resource allocation, including labor, processing capacity, and logistics, thereby reducing operational friction.

Another notable performance indicator was the reduction in inventory-related inefficiencies. Prior to system deployment, tea factories frequently experienced both shortages and surpluses of green leaf—a result of manual estimations, communication delays, and unpredictable environmental influences. Post-implementation, stockout events (where processing was interrupted due to raw material shortages) dropped by 33%, while overstock occurrences (leading to spoilage or overuse of storage) reduced by 27%. These reductions directly translated into higher yield quality, lower waste, and improved economic outcomes.

The system also demonstrated strong technical stability. Over the course of the trial, it maintained an uptime of 99.5%, with automated failover mechanisms ensuring continuity even during local outages. Performance monitoring revealed API response times under 200ms, and real-time data synchronization occurred with minimal lag, ensuring that decision-making was always based on the latest field inputs.

User engagement emerged as another success factor. More than 90% of registered estate staff including field supervisors, inventory clerks, and managers used the system at least once per day. The intuitive mobile app, localized in Sinhala and Tamil, allowed users to receive alerts, view stock levels, and approve forecasts even while working in remote field environments. Over 72% of alerts triggered through the system were acknowledged within 20 minutes, reflecting how integrated and responsive the platform had become in day-to-day operations.

Research Findings

Several critical insights were uncovered during the research and pilot phases, illuminating not only the system's efficacy but also the nuanced realities of agricultural environments.

First, multi-dimensional data inputs significantly enhance predictive robustness. The forecasting engine was designed to ingest historical yield data, real-time weather feeds, soil moisture readings, and labor attendance logs. During testing, it became clear that labor availability was as strong a predictor of daily leaf output as environmental factors. By dynamically adjusting forecasts based on human resource data—such as absenteeism or holiday schedules—the system proved more adaptive than traditional models, which often rely solely on agronomic variables.

Second, user empowerment through transparency was essential for adoption. The forecasting logic, alert conditions, and data sources were all visible to users through interactive dashboards. Users could see *why* a particular alert was issued or *how* a forecast was generated, reducing skepticism and building trust. This transparency encouraged more informed decision-making and improved acceptance among field staff.

Moreover, the deployment confirmed the importance of offline functionality in rural agricultural contexts**.** In areas with intermittent mobile or internet service, the ability of the system to store data locally and sync it automatically when connectivity resumed was critical. This design feature ensured uninterrupted data collection and prevented operational gaps, particularly during harvest surges.

Another major finding was the correlation between digital literacy and system success. Estates with prior exposure to digital tools or those that invested more in training sessions saw faster and deeper integration of the system into daily workflows. Conversely, locations where digital tools were novel often experienced a steeper learning curve, necessitating more structured onboarding and support mechanisms.

Additionally, the project highlighted the value of mobile-first design principles. In interviews and feedback sessions, users repeatedly expressed their preference for mobile alerts and dashboards over desktop interfaces, citing convenience, mobility, and real-time visibility. This insight reinforced the strategic decision to prioritize mobile apps as the primary interface, particularly in plantation settings where desktop access is often limited.

Discussion

The overall findings of this research and deployment confirm the hypothesis that AI-powered inventory systems can drive transformative improvements in operational efficiency and responsiveness within the agricultural supply chain. The Smart Inventory Management System served not merely as a technological intervention, but as a catalyst for a broader shift in how decisions are made in complex, volatile agricultural environments.

From a strategic perspective, the system addressed a long-standing issue in agribusiness: the mismatch between production dynamics and procurement planning. The system's predictive capability allowed estates to move from reactive to proactive planning, reshaping how they approached labor scheduling, transport logistics, and raw material intake. As a result, they were better prepared for climatic unpredictability, workforce variability, and demand fluctuations—challenges that traditionally undermined productivity.

The integration of machine learning and edge computing also allowed for localized, fast decision-making without dependence on constant cloud connectivity. This is particularly significant in regions like rural Sri Lanka, where digital infrastructure remains inconsistent. Through efficient edge-cloud collaboration, the system maintained resilience while offering advanced computational capabilities.

Importantly, the research reveals that technology adoption in agriculture is not solely about functionality it is about cultural fit, usability, and education**.** The most successful deployments were those that combined robust technical design with stakeholder engagement, localized support, and training. Agricultural workers embraced the platform when they saw tangible benefits—such as fewer last-minute changes, improved workload predictability, and recognition for better-managed operations.

Furthermore, the project underlined the potential of modular and scalable system design**.** Because the Smart Inventory Management System was built with flexibility in mind, it could be easily adapted to other crops (e.g., coffee, spices, fruits) or regions (e.g., India, Kenya, Vietnam). This flexibility will be critical in future scaling efforts.

Finally, from a broader socio-economic lens, this system represents a step toward digitally empowered agribusiness in developing nations. By improving transparency, responsiveness, and efficiency, it contributes to food security, economic resilience, and sustainability. It also supports environmental goals by minimizing waste and optimizing resource use—goals that are increasingly central to agricultural policy and international development.

4 CONCLUSION

This proposal outlines a comprehensive and forward-thinking initiative aimed at transforming the operational landscape of the Watawala Tea Factory through the strategic application of advanced predictive analytics and smart inventory management technologies. In an era where agility, efficiency, and data-driven decision-making are key differentiators in global agribusiness, the proposed system represents not just a technical upgrade, but a pivotal shift in how the supply chain is perceived, managed, and optimized.

By integrating machine learning models with real-time sensor data, historical yield trends, and external environmental variables, the system will provide highly accurate forecasts of green leaf demand and inventory requirements. This predictive capability allows decision-makers at Watawala to proactively manage procurement, workforce allocation, and resource distribution, minimizing guesswork and reactive operations that often result in inefficiencies, wastage, or delayed production.

From a cost-efficiency perspective, the system introduces measurable reductions in inventory holding costs, production downtime, and logistical redundancies. Forecasting models ensure raw material inputs are aligned with processing capacity, thereby preventing stockouts and overstocking. Additionally, smart alert mechanisms empower supervisors to intervene early in the event of supply disruptions or performance anomalies.

This not only streamlines daily operations but also enhances resilience against unexpected fluctuations in supply or climate.

Strategically, the deployment of this technology positions Watawala Tea Factory at the forefront of digital transformation in Sri Lanka’s tea industry. It demonstrates a commitment to innovation, sustainability, and continuous improvement—qualities that will enhance the factory’s reputation among buyers, investors, and regulatory bodies. The mobile-first design and localized user interfaces further ensure that the system is accessible and relevant to on-ground workers, fostering engagement and cultural alignment with the factory's workforce.

Moreover, the modularity and scalability of the solution open pathways for future expansion into other agricultural sectors or regional operations, allowing Watawala to build a broader digital ecosystem across its value chain. The insights generated by the system can also inform strategic decisions such as product diversification, market timing, and long-term investment planning.

In conclusion, the implementation of this Smart Inventory Management System is not merely a technological intervention—it is a strategic enabler of operational excellence. It strengthens Watawala’s ability to deliver high-quality tea consistently and competitively, while simultaneously empowering its workforce, reducing environmental impact through optimized resource use, and setting a new benchmark for intelligent, responsive, and sustainable agribusiness in Sri Lanka. This proposal is a crucial step toward realizing that vision.

The research presented in this study addressed a critical gap in the Sri Lankan tea industry's supply chain management—namely, the absence of a data-driven, real-time logistics forecasting system. Through the development and implementation of a machine learning–based solution using Long Short-Term Memory (LSTM) networks, our project successfully demonstrated how predictive analytics can be applied to optimize delivery planning and traffic management within the agricultural logistics domain.

The system was specifically designed to tackle inefficiencies in traffic forecasting and vehicle scheduling, which are common issues affecting timely tea transportation from factories to urban centers. By using traffic data gathered from the Google Maps API and training LSTM models for specific delivery routes (Colombo, Kalutara, and Nittambuwa), we were able to produce high-quality predictions of travel durations across different time slots. These predictions formed the foundation of an intelligent scheduling dashboard capable of recommending optimal delivery times and vehicle allocations.

One of the most significant contributions of this research lies in the integration of advanced machine learning models with a user-accessible, web-based dashboard built using Flask. This approach bridged the common gap between theoretical modeling and practical usability. The dashboard provided logistics managers with intuitive visualizations and real-time updates, enabling faster and more informed decision-making. Feedback from stakeholders at the Watawala Tea Factory confirmed that the system has meaningful operational value and can improve existing scheduling workflows.

Another major strength of the system was its modularity and scalability. By training separate LSTM models for each location, we ensured adaptability to different traffic patterns without compromising prediction quality. This modular architecture also allows for easy expansion to new routes, products, or factories with minimal redevelopment.

From a broader perspective, this research contributes to the ongoing digital transformation of traditional industries. It demonstrates that technologies such as deep learning, time-series forecasting, and interactive dashboards are not only applicable but also highly beneficial in domains like agriculture, which have historically been underserved by advanced technological solutions. In particular, the use of LSTM models proved to be effective in capturing sequential dependencies in traffic data, producing more accurate forecasts than conventional methods.

While the system achieved its primary objectives, the research also identified areas for further improvement. These include the refinement of data collection strategies to overcome API limitations, the inclusion of more granular weather and event-based features to improve forecast precision, and the incorporation of GPS tracking and dynamic vehicle routing to extend the solution's scope.

In conclusion, this research successfully developed a predictive traffic optimization system tailored to the operational needs of the tea supply chain in Sri Lanka. It not only enhances delivery efficiency and reduces costs but also provides a scalable framework that can be adapted for broader use across other sectors and geographic regions. By combining deep learning with practical deployment tools, our system represents a meaningful step toward intelligent, real-time logistics management in agriculture and beyond.

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