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Article

A Novel Intelligent Agent Equipped with Machine Learning for Route Optimization in Effective Supply Chain Management for Seasonal Agricultural Products

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Abstract: The ever-changing context of contemporary supply chain management, effective route optimization has emerged as a crucial component for companies looking to improve their operational efficiency. A challenging issue is presented by the complicated web of transportation networks, a variety of delivery places, and constantly shifting parameters like Temperature, Humidity etc. The combination of cutting-edge technology, particularly Machine learning (ML), deep learning (DL) and Artificial intelligence (AI), has emerged as a game-changing option to solve. This project presents the comparative analysis of machine learning including deep learning model for reference of accuracy, the models specifically designed for crop prediction are implied and artificial intelligence algorithms for supply chain management route optimization. This method seeks to transform the way and distribution networks are managed by utilizing historical route data, real-time information, and sophisticated learning algorithms. The ultimate goal is to introduce efficiencies that transcend traditional approaches, resulting in improved efficiency in delivery times, and optimal management of agricultural seasonal inventory. Through the seamless integration of ML, DL and AI technologies, this innovative solution endeavors to break the complexity level of contemporary supply chain management, ushering in a new era of operational excellence and efficiency.

Keywords: supply chain management; artificial intelligence (AI); machine learning (ML); deep learning (DL); route optimization; seasonal product management; real-time dataset

1. Introduction

The integration of machine learning, deep learning and artificial intelligence domain is a key exploration in supply chain management of seasonal products This project introduces machine learning algorithms, deep learning algorithm-based crop prediction artificial intelligence route optimization in the effective supply chain especially in management of seasonal agricultural products. As seasonal products demand a unique logistical approach, the proposed system aims to enhance efficiency and reduce operational time by dynamically optimizing transportation routes. Through this proposed approach, the project addresses the specific challenges posed by seasonal agricultural products in the supply chain, ultimately improving overall productivity and customer satisfaction.

In this context, this research proposes a crop recommendation integrated based on machine learning algorithms, deep learning algorithm that uses chemical levels in the soil, environmental variables that helps in crop data to determine the optimal crop for a specific region. This system is designed to be adaptable, expandable and resilient, allowing for easy management of seasonal products as it proposes integration of route optimization and then integrated to artificial intelligence algorithms for route optimization considering the source and destination state along with the route information which helps the Supply chain management sector to validate and explore their structure of efficient function of the supply of seasonal goods.

This research focuses to integrate a crop recommendation system that leverages weather and soil data to improve crop selection, where the dataset contains different variable values for every specific state and crop and yield in agriculture with respective to specific states by training the machine learning and deep learning models, integrated model displays the cities through it can reach the destination as a best solution among the other routes by implying artificial intelligence algorithms. By putting the proposed system through practical testing and validation, the research aims to validate its effectiveness and highlight its potential for widespread use in the supply chain management sector.

Furthermore, the structured architecture of the crop prediction system integrated with route optimization streamlines the reuse of code and its ability to grow. The system can effortlessly expand to integrate more weather and soil variables, depending upon the transportation method, transportation metrics vehicle or to factor in alternative elements like pest control, water availability, and market trends, wage cost, petrol diesel cost. Its adaptable structure allows for smooth integration with diverse agricultural sectors in supply chain management platform. The proposed system is designed using advanced machine learning techniques and algorithms, along with deep learning for crop prediction and the deep learning algorithm is integrated with Artificial intelligence including Decision Trees, Random Forests, Naïve Bayes, (KNN) K Nearest Neighbor, Agglomerative Clustering and LSTM algorithms integrated with Ant colony optimization ,Artificial Bee Colony optimization ,simulated annealing to predict the optimal crop and route based on the input parameters. The system undergoes training using historical data, and its weather and soil data, and data collected with approximate distance and route information from source state to destination state guaranteeing the precision and promptness of the suggestions. In summary, the suggested crop recommendation and route optimization system, employing an intelligence-assisted strategy, proves to be a potent asset for the supply chain management sector to maintain a quality-based service to farmers and agricultural experts. It streamlines the crop selection process, mitigates risks, and enhances yields, ultimately contributing to enhanced seasonal products management through route optimization creating a visual idea of how the route optimization among the states are done which is a vision of economic advancement in the agricultural sector and supply chain management playing a booster key component.

2. Literature Survey

The research in [1] gives the insights for the optimal urban route planning, surpassing genetic algorithm, particle swarm optimization, and artificial neural networks in efficiency, decision making, and stability taking time to process.

The brief ideology in [2] gives insights regarding the (PRM), Ant Colony Optimization (ACO), and B-spline curve. ACO can be adapted to dynamic environments as it uses pheromone deposition and evaporation to adapt to changing conditions is suitable for static environments, making it applicable to a wide range of scenarios where the environment is known.

The study in [3] explores AI and ML applications in supply chain stages, employing neural networks and genetic algorithms while identifying adoption barriers. Emphasizing practical, social, and theoretical implications, it highlights their diverse impact on optimization, predictive analytics, and decision-making frameworks. Integrating ML-based supplier selection models into existing procurement processes may face challenges related to organizational resistance and the need for adjustments in workflow.

The paper in [4] presents the evolution of path planning algorithms for mobile robots, with a focus on grid-based environments and the introduction of the ABACO algorithm. ABACO extends ACO by introducing the concept of ant aging. Older ants contribute less to pheromone updates, encouraging exploration and reducing the influence of non-optimal solution may suffer from slow convergence and exploration challenges in large solution spaces. The algorithm is based on the probabilistic technique and is inspired by the Ant Colony Optimization (ACO) as a metaheuristic algorithm inspired by the observing behavior of ants. This algorithm found applications in solving various optimization problems, including vehicle routing, traveling salesman, traffic assignment, shortest path While ACA is effective, it may require fine-tuning parameters for different problem instances. Additionally, its convergence to the optimal solution might depend on problem characteristics. Linear Programming methods, such as the Simplex Method, can become computationally intensive for large-sized problems.

The insights in [5] conveys the algorithm found in applications in solving various optimization problems, including vehicle routing, traveling salesman, traffic assignment, shortest path, and minimum spanning tree problems. MACOA aims to provide solutions closer to optimality with fewer iterations. It is designed to handle both balanced and unbalanced TP. Comparative studies provide insights into the relative performance of different algorithms for TP. While ACA is effective, it may require fine-tuning parameters for different problem instances. Additionally, its convergence to the optimal solution might depend on problem characteristics. Linear Programming methods, such as the Simplex Method, can become computationally intensive for large-sized problems.

The brief information in [6] uses a dueling deep Q network to learn strategies for avoiding congested roads, resulting in a 52%-time savings compared to traditional shortest path planning algorithms under congestion conditions. The DARP algorithm, leveraging deep reinforcement learning, achieves substantial time savings (52%) under congestion, demonstrating significant improvements in travel time efficiency. In this, the time variable is the only main parameter considering the obstacles.

The research study in [7] introduces an innovative solution, integrating machine learning and road network optimization through reinforcement learning, to dynamically enhance traffic flow in real time, demonstrating significant travel time reduction across diverse scenarios with computational efficiency. The proposed CLLA+ algorithm's compatibility with partially autonomous vehicles suggests a phased approach to implementation. It acknowledges the coexistence of autonomous and human-driven vehicles. Challenges include the need for widespread adoption of CAV technology, addressing cybersecurity concerns, and managing the transition period with mixed fleets of autonomous and human-driven vehicles.

The paper [8] presents a sustainable supply chain optimization tool employing the Floyd-Warshall algorithm, utilizing nodes and vertices for location and path modeling, respectively, and integrating the Google Maps platform for route recommendations. Enables continuous communication and modification of routes, resulting in optimized transportation costs, reduced delivery times, minimized waste, improved fuel economy, and lower atmospheric emissions. Enables continuous communication and modification of routes, resulting in optimized transportation costs, reduced delivery times, minimized waste, improved fuel economy, and lower atmospheric emissions.

The research in [9] data-driven framework utilizes gradient boosted regression tree methodology to enhance implication at the warehouse level, considering costs with respect to loss in the market value, extra baggage stock, and When the characteristics of the reference and target series significantly differ. The effectiveness of transfer learning might be constrained in certain situations.

One of the research works [10], provides a brief idea of reinforcement learning algorithms and their applications in supply chain management the black-box nature of some reinforcement learning models can pose challenges in interpreting and understanding the decision-making rationale.

The case study in [11] The proposed Deep Reinforcement Learning model for Drug inventory (DRLD) combines RL and DNN to automate drug inventory decisions, outperforming baseline approaches in reducing refilling costs and shortage situations through intensive simulations. Lacks specific details about the mathematical or technical aspects of the proposed Dynamic Refilling drug Optimization (DR2O) and Deep Reinforcement Learning model for Drug inventory (DRLD).

The research study [12] paper explored and briefed the challenges and opportunities in implementing machine intelligence-based routing in future networks, addressing the limitations of current architectures and protocols.

The study in [13] encompasses deterministic linear programming models (DLP), multi-stage stochastic programs (MSSP), reinforcement learning (RL), and extensions to address multi-echelon problems. Notable contributions include works by Hubbs et al. in supply chain optimization using these methodologies, alongside their efforts in extending IMPs within the OR-Gym open-source project. These diverse approaches offer insights into optimizing inventory management and addressing the complexities of modern supply chains. Researchers can leverage these sources for developing effective solutions in supply chain optimization.

A comprehensive framework was proposed for applying machine learning (ML) algorithms in various aspects of supply chain management (SCM) [14]. It evaluates the efficiency of traditional versus AI methods in handling big data, reviews and classifies commonly used AI techniques in SCM, and presents a detailed framework for applying ML techniques in supplier selection, risk prediction, demand forecasting, and other SCM domains.

The research study put forward in [15] proposes a novel approach by combining deep reinforcement learning (DRL) with a Recurrent Neural Network (RNN) for crop yield prediction. It introduces a Deep Recurrent Q-Learning model, integrating RNN capabilities to process temporal data effectively. By leveraging experience replay and L1 regularization, the DRL training process is stabilized, ensuring efficient learning and adaptation of the yield prediction agent. These modifications enhance the agent's ability to learn from experiences and improve prediction accuracy in agricultural settings.

An ANN based Method for improving crop yield prediction accuracy to forecast crop yield (CY) using temperature, climate, and soil features, employing various machine learning (ML) algorithms was proposed [16]. It conducts a comparative analysis of ML algorithms to evaluate prediction accuracy, with a focus on enhancing CY prediction accuracy. Relevant literature includes studies on crop yield prediction using ML techniques, highlighting the importance of input features and algorithm selection in achieving accurate forecasts.

The case study in [17] conducts a comprehensive literature review on the trends of machine learning (ML) applications in supply chain management (SCM). ML algorithms are recognized and ordered by frequency of use in SCM, followed by an exploration of their features and applications in key SCM activities such as demand estimation, procurement, production, inventory management, transportation, and supply chain enhancement.

The study in [18] acknowledges the need for further exploration of potential limitations and challenges in the proposed AI/ML-based methods, with a potential gap in addressing specific practical constraints in certain scenarios.

The domain of research in [19] presents a range of studies exploring the implication of (AI) in various domains also investigates the use of drone swarm intelligence in agriculture, explores the impact of AI system automation on gig work engagement and satisfaction, while Xia et al. analyzed the optimization and lean planning with machine learning. Helo and Hao provide insights into AI-driven supply chain management through case studies.

A survey [20] was conducted to provide reviews and the significance of neural networks, in various aspects of agricultural management, including crop yield prediction, disease identification, and climate mapping for crop suggestion. They contribute to the advancement of precision agriculture and sustainable crop production practices.

The interest of research paper in [21] provides comprehensive insights into deep learning techniques, recurrent neural networks (RNNs), for agricultural yield prediction. For computer vision tasks. It covers the fundamentals of CNN architecture.

The proposed methodology in [22] addresses the limitations of lumped parameter models in predicting spatial characteristics, Control Flow Diagram (CFD) has been widely adopted. Studies have used CFD to model greenhouse climate, predict solar heat load and temperature fields, and optimize climate control schemes for crop growth. CFD has been employed to study dynamic solar heat load, temperature distribution, and optimal north wall thickness in solar greenhouses.

The information of research in [23] provides a comprehensive overview of various machine learning algorithms, including linear regression, decision trees, gradient boosting, random forests, and ensemble methods. It covers the theoretical foundations, practical implementations, and applications of these algorithms in predictive modeling tasks.

The research study in [24] covers topics in logistics and supply chain management, including transportation, distribution, inventory management, and strategic planning. While it does not delve into specific algorithms, it likely discusses optimization techniques such as linear programming, network optimization, and heuristic methods used to optimize transportation routes, inventory levels, and distribution networks.

The research of information in [25] proposes a Stable Matching Based Resources Allocation (SMRA) model for large-scale Fog environments, focusing on optimizing resource allocation for IoT devices. Inspired by existing research, it utilizes the Gale-Shapley algorithm and makes key assumptions about the static topology and interlaced structure of Fog nodes. The proposed SMRA architecture involves clustering Fog nodes based on geographical proximity, assigning roles to nodes, batch processing requests, and performing matching to redirect requests efficiently. This approach addresses the challenge of dynamic resource management in Fog networks, aiming to improve service delivery for IoT applications.

The case study in [26] compares various prediction models for wind power forecasting, including Fluid Dynamic, Fuzzy Logic and Back Propagation Neural Network (BPNN) with ARMA, Empirical Mode Decomposition, and Support Vector Machine. Results indicate that ARMA performs best among neural network models, while Empirical Mode Decomposition outperforms Support Vector Machine with a significantly lower error rate. The study emphasizes the importance of accurate wind prediction for renewable energy production and explores different mathematical techniques to improve forecasting accuracy, highlighting the potential of hybrid approaches like ANFIS and LSTM networks.

A case study has been conducted in [27] to compare two algorithms, EHOIF and EEHOLSIF, for information foraging on social media. Results show that EEHOLSIF outperforms EHOIF based on Rate, and response time, attributed to enhancements like the territory concept and migration mechanism. Additionally, a comparative study with an Ant Colony System (ACS) approach adapted for information foraging on social media highlights the superior performance of EEHOLSIF in terms of relevance score and response time.

The put forward study in [28] encompasses processes converting raw materials into finished goods. MI is categorized by the number of workers, influencing input costs (IC), gross output value (VGO), value added (VA), and labor costs (LC). Data Analysis Model (DAM) employs Statistical Analysis (SA), including Descriptive Analytics (DsA) for data distribution, Diagnostic Analytics (DcA) for identifying causes, Predictive Analytics (PdA) for forecasting future events, and Prescriptive Analytics (PcA) for recommending actions. Techniques such as K Means Clustering, Naïve Bayes Classifier, Linear Regression, and Monte Carlo Simulation are used for different analytics tasks in DAM, each offering distinct advantages and suitability for various analyses.

The study in [29] explores the Manufacturing Industry (MI), its categorization based on workforce size, and associated factors like input costs (IC), gross output value (VGO), value added (VA), and labor costs (LC). It introduces the Data Analysis Model (DAM) encompassing Statistical Analysis (SA), including Descriptive Analytics (DsA), Diagnostic Analytics (DcA), Predictive Analytics (PdA), and Prescriptive Analytics (PcA). Various techniques like K Means Clustering, Naïve Bayes Classifier, Linear Regression, and Monte Carlo Simulation are employed for different analytics tasks within DAM, offering comprehensive insights into MI operations and decision-making processes.

The survey and implication of proposed ideology in [30] reviews the application of multi-objective evolutionary algorithms and metaheuristics in feature selection, encompassing a range of techniques such as genetic algorithms, particle swarm optimization, and simulated annealing. It explores their efficacy in various computer science domains. Through an analysis of existing research, the paper elucidates how these optimization techniques contribute to enhancing feature selection processes, offering valuable insights for improving computational tasks reliant on feature selection methodologies.

3. Proposed Work

3.1. Crop Recommendation System Integrated with Route Optimization

The proposed crop recommendation and route optimization system enhances various innovative features, including soil and weather analysis, route optimization, and the determination of the optimal path among multiple routes to reach the destination state from the source state.

1. Machine learning: Weather and soil data to recognize the patterns and predict which crops are best suited for particular conditions.
2. Deep learning: Weather and soil data to recognize the patterns and predict about which crops are best suited for particular conditions for this process one of the algorithms that gives the same accuracy as the machine learning algorithm that gives the maximum accuracy has been chosen and implemented.
3. Artificial intelligence: Novelty could be the use of Artificial intelligence algorithms to analyze the data and provide recommendations. These algorithms could be trained on large datasets of historical information of routes, distance and via cities through which the supply takes place from source to destination.
4. Route recommendation: Gives the optimal solution for the seasonal product to reach the destination state in short period of time compared to the different available routes as the seasonal products can retain only for some period of time. The process of selecting optimal route considers the parameters of values with least distance and highest crop price.
5. Real-time updates: Another basic novelty would be the use of historical data to provide recommendations based on weather and soil conditions and approximate transportation metrics information of routes from state to state gathered for the implication of this particular project. This could allow supply chain management industry to make more informed decisions about planting, harvesting, structured implementation of supply of seasonal goods enhancing the service and quality of goods satisfying customers.

Overall, a crop recommendation and route optimization system that integrates soil and weather content has the potential to revolutionize agriculture by providing farmers with more accurate and targeted recommendations, enabling them to make more informed decisions and improve crop yields.

3.2. Proposed Methodology

Research question: The supply chain management sector faces significant challenges in managing the supply chain of seasonal products efficiently. One critical aspect is the transportation of these seasonal agricultural goods from farms to distribution centers. The dynamic nature of various environmental conditions and availability of many routes with variable distance metrics, this Brings necessity of an intelligent solution for route optimization. Traditional methods struggle to adapt to the complexity and variability inherent in the seasonal agricultural supply chain.

Data collection: collecting the dataset from Kaggle and some variable approximate data values gathered from internet.

Model development: Develop a model for generating crop recommendations and route optimization using the selected algorithm(s), incorporating features such as crop suitability, climate suitability, and soil fertility, distance. Train the model on previous data along with the approximate data collected and validate efficiency based on values of accuracy, precision, recall, and F1 score.

Comparison with traditional methods: Analyze machine learning-based crop recommendation system and artificial intelligence implying route optimization with traditional methods such as expert knowledge or rule-based systems.

Interpretation and analysis: Interpret the results of the study and analyze the implications for supply chain management sector. Consider the potential benefits and drawbacks of using machine learning-based crop recommendation systems and the importance of ongoing study and enhancement in this area.

Summarize the key findings of the study: This will provide recommendations for the supply chain management industry to structure the operational functionality. Highlight the potential benefits of using data-driven approaches for crop recommendation and route optimization and the importance of ongoing research and development in this area.

3.3. Proposed Framework

The proposed framework contains three major components:

- Implementing Seasonal products prediction by the means of applying DL and ML algorithms for data analysis
- Application of optimization algorithm to find the optimal route using Artificial intelligence
- Decision making and recommendation

The proposed framework is depicted in Figure 1 demonstrates the phases of the implementation of different phases of implementation. There are three different phases.

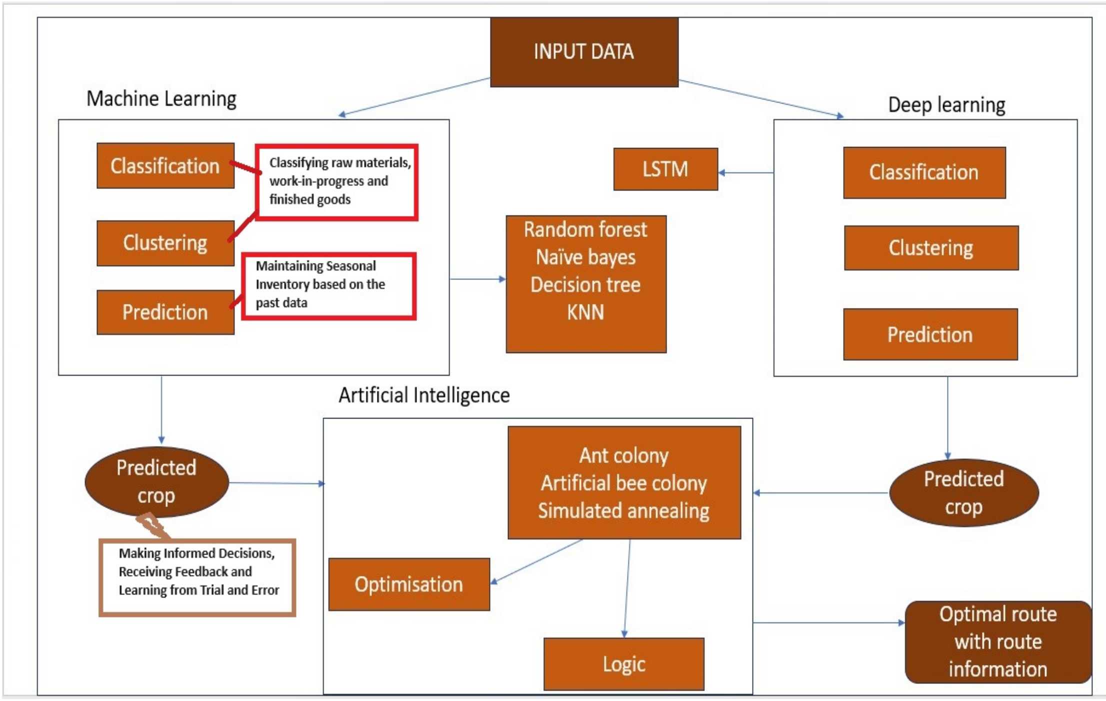

Figure 1. Key Components Interaction in the Proposed Recommendation System.

1. PHASE I: The first phase of the project is Machine learning and deep learning domain where the crop prediction takes place by taking into consideration of the historical data-based analysis consisting of the chemical elements level in the soil, environmental variables like, nitrogen (N_Soil), phosphorous (P_Soil), Potassium level(K_Soil) levels in soil, humidity, rainfall level.
2. PHASE II: The second phase is integrating the result obtained in the first phase The predicted crop with the source destination is fed to Artificial intelligence algorithms for this data analysis is done from Kaggle and google referring to the distances between the states and route information through which the supply transportation has to pass through to obtain the destination optimal route with lowest distance and greater crop price which is considered to have the optimal profit.

3. PHASE III: Decision and recommendation making phase where the decision of the best route among the available routes is made and recommends the best destination displays the output with the following information of destination state, price, distance, route information through the cities the transport has to pass by.

3.4. Methodology Applied

3.4.1. Machine Learning

Naive Bayes

Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem, which describes the probability of an event based on prior knowledge of conditions that might be related to the event.

$$P\ (y|x1, x2, \ldots, xn)\ =\ (P(x1|y)\ *\ P(x2|y)\ *\ P(xn|y)\ *\ P(y))\ /\ P\ (x1, x2, \ldots xn) \tag{1}$$

In Equation (1) P (y|x1, x2, ..., xn) is the posterior probability of class y given features x1, x2, ..., xn
P (x1, x2, ..., xn|y) is the likelihood
P (y) is the prior probability of class y
P (x1, x2, ..., xn) is the evidence probability

Decision Tree

A Decision Tree algorithm doesn't have a single formula like some statistical models. Instead, it builds a tree-like structure based on decision rules.

Like The data is then split into branches based on the outcome of the decision rule. For instance, one branch could represent "Yes" (temperature > 25 °C), and the other "No" (temperature ≤ 25 °C). The Equations (2) and (3) provides the calculation of Gini Index and Entropy respectively.

$$\text{G}ini\ \text{I}ndex = 1 - \sum(\text{pi})^{\wedge}2 \tag{2}$$

$$\text{En}tropy\ (s) = -\sum\ (\text{pi}\ \log2(\text{pi}) \tag{3}$$

K Nearest Neighbor

K-Nearest Neighbors (KNN) In the context of agricultural products inventory maintenance, KNN can be employed for tasks such as categorizing products based on demand patterns, predicting inventory needs, or identifying similar products for seasonal supply chain optimization.

KNN classifies or predicts depending on the highest-class value or average value of the k-nearest data points in the feature space.

Distance Metric: It relies on a distance value (mostly Euclidean distance) to measure the similarity or closeness between data points.

Decision Rule: For classification, the decision rule might be "Assign the most common class among the k-nearest neighbors". For regression, it could be "Predict the average value of the k-nearest neighbors".

Euclidean Distance

$$(x, y)\ =\ \sqrt{}(\ 〖(x\_1 - x\_2)〗^{\wedge}2 +\ 〖\ (y\_1 - y\_2)〗^{\wedge}2) \tag{4}$$

Manhattan Distance

$$(x, y)\ =\ |x\_1 - x\_2\,| + |y\_1 - y\_2\,| \tag{5}$$

Equations (4) and (5) Represent the function used to find the distance to find the nearest neighbor.

Random Forest

Random Forest mitigates the risk of individual trees being biased, resulting in robust and reliable predictions.

The algorithm can accurately classify crops, offering valuable insights for agricultural planning and decision-making. Through ensemble learning from multiple decision trees, Random Forest enhances predictive accuracy and generalization, enabling farmers and researchers to make informed decisions regarding crop selection and management practices. This approach fosters more enhancement in the implication of agricultural activities by leveraging data-driven insights to optimize crop yield and quality.

3.4.2. Deep Learning

Long Short-Term Memory (LSTM)

The LSTM algorithm utilizes a set of gates, including input, forget, and output gates, along with a memory cell, to regulate the flow of information through the network. The key equations governing the LSTM cell dynamics are as follows:

$$Ct = ft \cdot Ct - 1 + it \cdot C.t \tag{6}$$

Equation (6) represents Ct is the cell state at time step t,
ft is the forget gate at time step t,

- −1Ct−1 is the cell state from the previous time step,
- it is the input gate at time step t,
- C~t is the candidate cell state at time step t.

3.4.3. Artificial Intelligence

Ant Colony Optimization

Ant Colony Optimization (ACO) can be applied to agricultural seasonal inventory management for optimizing routes, logistics.

Adaptation: Over iterations, the algorithm adapts to find optimal paths. The balance between exploration (choosing less explored paths) and exploitation (choosing paths with higher pheromone levels) is crucial.

Application in Agricultural Inventory: In the context of agricultural products, ACO can optimize transportation routes, ensuring efficient delivery and distribution during different seasons.

Dynamic Adaptation: It can dynamically adapt to changes in demand, seasonality, or other factors affecting agricultural supply chains. ACO in agricultural seasonal inventory management optimizes routes and resource allocation by following the cooperative foraging behavior of ants. The algorithm dynamically adapts to changes in the environment and helps find efficient solutions for the transportation and distribution of agricultural products.

Artificial Bee Colony

The ABC algorithm is designed to find optimal solutions through the imitation of the foraging behavior of honeybees. In the context of agricultural seasonal inventory management, ABC can be applied for optimizing tasks such as resource allocation, route planning, or other logistics-related challenges.

Objective Function: Minimize the total transportation cost considering factors like distance, time, and seasonal constraints. Where Total Cost could be a function considering distances, transportation time, and seasonal factors. Explore the neighborhood of current routes to improve transportation efficiency. Adjust the current route based on the difference between its position and that of another randomly chosen route.

Simulated Annealing

Simulated Annealing is a metaheuristic optimization. It's commonly used for solving combinatorial optimization problems like route optimization. Here's a brief overview of how Simulated Annealing works for route optimization.

Neighborhood Generation: Generate a neighboring solution by making a small change to the current solution. In route optimization, this could involve swapping two locations in the route or reversing the order of a subset of locations.

Acceptance Criterion: Determine whether to accept the new solution as the current solution. Simulated Annealing uses a probabilistic criterion based on the change in objective function value and a parameter called the temperature. Initially, solutions that increase the function value may be utilised to explore the search space, but as the algorithm progresses, only solutions that decrease the objective function value are accepted.

Termination: Repeat steps 3 to 5 for a predefined number of iterations or until a stopping criterion is met. This could be a more loop of functioning, attaining a certain temperature threshold, or achieving a satisfactory solution.

Simulated Annealing is a stochastic optimization algorithm, meaning that it introduces randomness into the search process to escape local optima and explore the solution space more effectively. By gradually decreasing the temperature, the algorithm transitions from exploration to exploitation, ultimately converging to a near-optimal solution for the given optimization problem.

3.5. Proposed Route Optimization Algorithm

In Figure 2 the process of implementation is as follows:

This project is started from the data set created and then fed to machine learning algorithms. Naive bayes, random forest, decision tree, K nearest neighbor, long short-term memory (LSTM) is implied for crop prediction.

The crop predicted is then fed to Artificial intelligence algorithm. The Source state is given along with the predicted crop considered from the dataset the Distance and crop price is evaluated.

a. The destination with high cost and low distance is obtained to be the optimal solution.
b. The output information that will be displayed Destination, price, route information (i.e. through which cities the transportation to be done to reach the nearest destination).

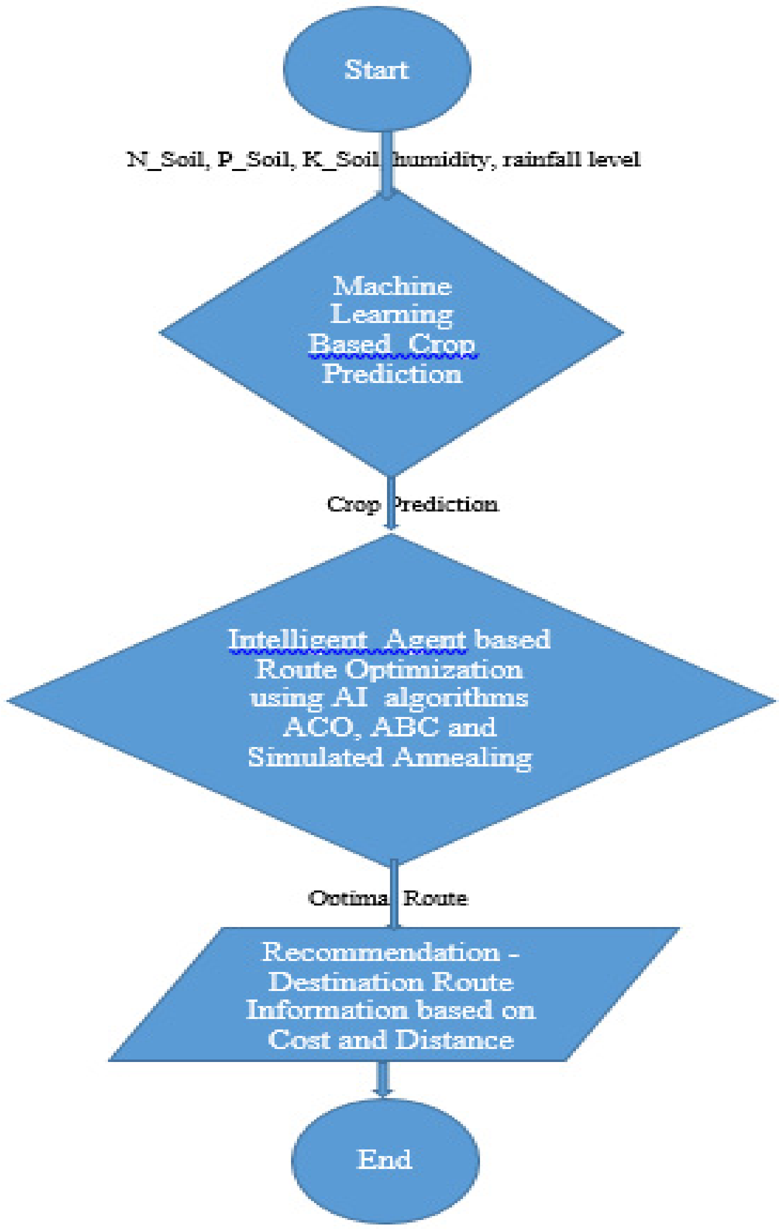

Figure 2. Proposed crop recommendation and route optimization.

3.6. Experimentation and Result Analysis

3.6.1. Case Study

Dataset Description

In [31] the created data set for this research and implication is available. Description of the information in Table 1 contains 2,200 variable values with the purpose and role of it in the implementation are being explained in brief.

pH: pH level of the soil. pH is a measure of soil acidity or alkalinity, with values below 7 indicating acidity, and values above 7 indicating alkalinity.

HUMIDITY: Humidity is the amount of water vapor present in the air.

N_SOIL: Nitrogen content in the soil. Nitrogen is an essential nutrient for plant growth and is often required in relatively large amounts.

P_SOIL: Phosphorus content in the soil. Phosphorus is another essential nutrient for plant growth, particularly important for root development and flowering.

K_SOIL: Potassium content in the soil.

RAINFALL: Rainfall is critical for providing water to crops, but excess or insufficient rainfall can have adverse effects on crop yield.

TEMPERATURE: Temperature of the environment. Temperature influences various physiological processes in plants, such as growth rate, flowering, and fruiting.

STATE: State or region where the crops produced is collected.

DESTINATION: Destination or market where the crops are intended to be sold or transported. This feature is used for route optimization.

VIA1, VIA2, VIA3: Intermediate waypoints or stops along a transportation route. These features are used for route optimization.

PRICE: Price of the crops in the market. This feature represents the economic value of the crops and can be used for crop prediction and optimization strategies.

Table 1. Dataset information.

pH.	RAINFALL	STATE	CROP PRICE	CROP	DESTINATION	DISTANCE	VIA1	VIA2	VIA3
6.502985	202.9355	Andaman and Nicobar	7,000	Rice	Andhra Pradesh	2,150	Port Blair	Chennai	Visakhapatnam
7.038096	226.6555	Andaman and Nicobar	5,000	Rice	Andhra Pradesh	1,780	Port Blair	Chennai	Vijayawada
7.840207	263.9642	Andaman and Nicobar	7,000	Rice	Tamil Nadu	1,700	Port Blair	Chennai	Madurai
6.980401	242.864	Andaman and Nicobar	7,000	Rice	West Bengal	2,700	Port Blair	Chennai	Kolkata
7.628473	262.7173	Andaman and Nicobar	120,000	Rice	Andhra Pradesh	1,780	Port Blair	Chennai	Vijayawada
7.073454	251.055	Andaman and Nicobar	3,500	Rice	West Bengal	1,700	Port Blair	Visakhapatnam	Kolkata
5.700806	271.3249	Andaman and Nicobar	7,500	Rice	West Bengal	2,700	Port Blair	Chennai	Kolkata
5.718627	241.9742	Andaman and Nicobar	6,500	Rice	Tamil Nadu	1,200	Port Blair	Chennai	Madurai
6.685346	230.4462	Andaman and Nicobar	10,000	Rice	Tamil Nadu	1,200	Port Blair	Chennai	Madurai

These features provide important information about the soil, environment, geography, and market conditions, which are essential for predicting crop yield and optimizing transportation routes for efficient crop delivery.

ML model to find out the suitable crop after trained. The result of the implementation of a specific crop predicted and route optimization done is shown below.

As the prediction of crop is done instantaneously it get integrated to do the route optimization with the nearby state's destination.

The optimal route will be found buy considering the profit price in the market and least distance value

In the Figure 3 depicts the example implementation where maize is being predicted as the crop type based on the environmental variables according the implementation 55 iterations are being done.

```
55/55 [==============================] - 0s 8ms/step - loss: 0.1233 - accuracy: 0.9773 - val_loss: 0.1617 - val_accuracy: 0.9545
Epoch 35/50
55/55 [==============================] - 1s 13ms/step - loss: 0.1196 - accuracy: 0.9756 - val_loss: 0.1625 - val_accuracy: 0.9545
Epoch 36/50
55/55 [==============================] - 1s 16ms/step - loss: 0.1132 - accuracy: 0.9807 - val_loss: 0.1524 - val_accuracy: 0.9591
Epoch 37/50
55/55 [==============================] - 1s 13ms/step - loss: 0.1098 - accuracy: 0.9795 - val_loss: 0.1508 - val_accuracy: 0.9568
Epoch 38/50
55/55 [==============================] - 1s 10ms/step - loss: 0.1063 - accuracy: 0.9795 - val_loss: 0.1523 - val_accuracy: 0.9545
Epoch 39/50
55/55 [==============================] - 0s 8ms/step - loss: 0.1025 - accuracy: 0.9784 - val_loss: 0.1539 - val_accuracy: 0.9568
Epoch 40/50
55/55 [==============================] - 0s 8ms/step - loss: 0.1022 - accuracy: 0.9790 - val_loss: 0.1561 - val_accuracy: 0.9545
Epoch 41/50
55/55 [==============================] - 0s 8ms/step - loss: 0.0958 - accuracy: 0.9812 - val_loss: 0.1435 - val_accuracy: 0.9591
Epoch 42/50
55/55 [==============================] - 0s 8ms/step - loss: 0.0943 - accuracy: 0.9824 - val_loss: 0.1394 - val_accuracy: 0.9614
Epoch 43/50
55/55 [==============================] - 1s 9ms/step - loss: 0.0931 - accuracy: 0.9835 - val_loss: 0.1388 - val_accuracy: 0.9591
Epoch 44/50
55/55 [==============================] - 0s 8ms/step - loss: 0.0889 - accuracy: 0.9824 - val_loss: 0.1378 - val_accuracy: 0.9614
Epoch 45/50
55/55 [==============================] - 0s 9ms/step - loss: 0.0858 - accuracy: 0.9852 - val_loss: 0.1371 - val_accuracy: 0.9568
Epoch 46/50
55/55 [==============================] - 0s 8ms/step - loss: 0.0854 - accuracy: 0.9835 - val_loss: 0.1387 - val_accuracy: 0.9614
Epoch 47/50
55/55 [==============================] - 0s 9ms/step - loss: 0.0827 - accuracy: 0.9847 - val_loss: 0.1284 - val_accuracy: 0.9614
Epoch 48/50
55/55 [==============================] - 0s 9ms/step - loss: 0.0805 - accuracy: 0.9852 - val_loss: 0.1222 - val_accuracy: 0.9659
Epoch 49/50
55/55 [==============================] - 0s 8ms/step - loss: 0.0798 - accuracy: 0.9801 - val_loss: 0.1199 - val_accuracy: 0.9659
Epoch 50/50
55/55 [==============================] - 0s 8ms/step - loss: 0.0757 - accuracy: 0.9847 - val_loss: 0.1274 - val_accuracy: 0.9636
1/1 [==============================] - 1s 1s/step
Predicted Crop: Maize
```

Figure 3. Prediction of the Crop.

As we can see in Figure 4 The predicted crop is integrated with the AI model algorithms then the source state is being given whereas in the above case the source state is Gujarat as input and the destination state along with the route information, price is being displayed.

The above process is initiated with the implication of Machine learning algorithms which are Random Forest, Naive Bayes, Decision tree, KNN and LSTM a Deep learning Algorithm. Among the Machine Learning Algorithms Random Forest has the maximum accuracy along with the LSTM algorithm from deep learning is being implied obtains the same maximum accuracy.

As this project integrates Machine learning, deep learning to Artificial intelligence the output obtained of predicted crop is fed to the artificial intelligence algorithms then by considering the parameter values of crop price and distance the optimal route is obtained displaying the result of destination state, Distance, crop price and route information as shown in figure.

```
Iteration 71/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 72/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 73/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 74/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 75/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 76/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 77/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 78/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 79/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 80/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 81/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 82/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 83/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 84/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 85/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 86/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 87/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 88/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 89/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 90/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 91/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 92/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 93/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 94/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 95/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 96/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 97/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 98/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 99/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Iteration 100/100: Best Distance = 430.0, Best Price = 2817.6451612903224
Best Solution:
Destination: Rajasthan
Distance: 430.0
Price: 2817.6451612903224
Vias: ['Ahmedabad', 'Vadodara', 'Udaipur']
```

Figure 4. Output of the optimal route for the predicted crop.

From the Figure 5 results we can infer the predicted crops according to the environmental and soil value are depicted in graph.

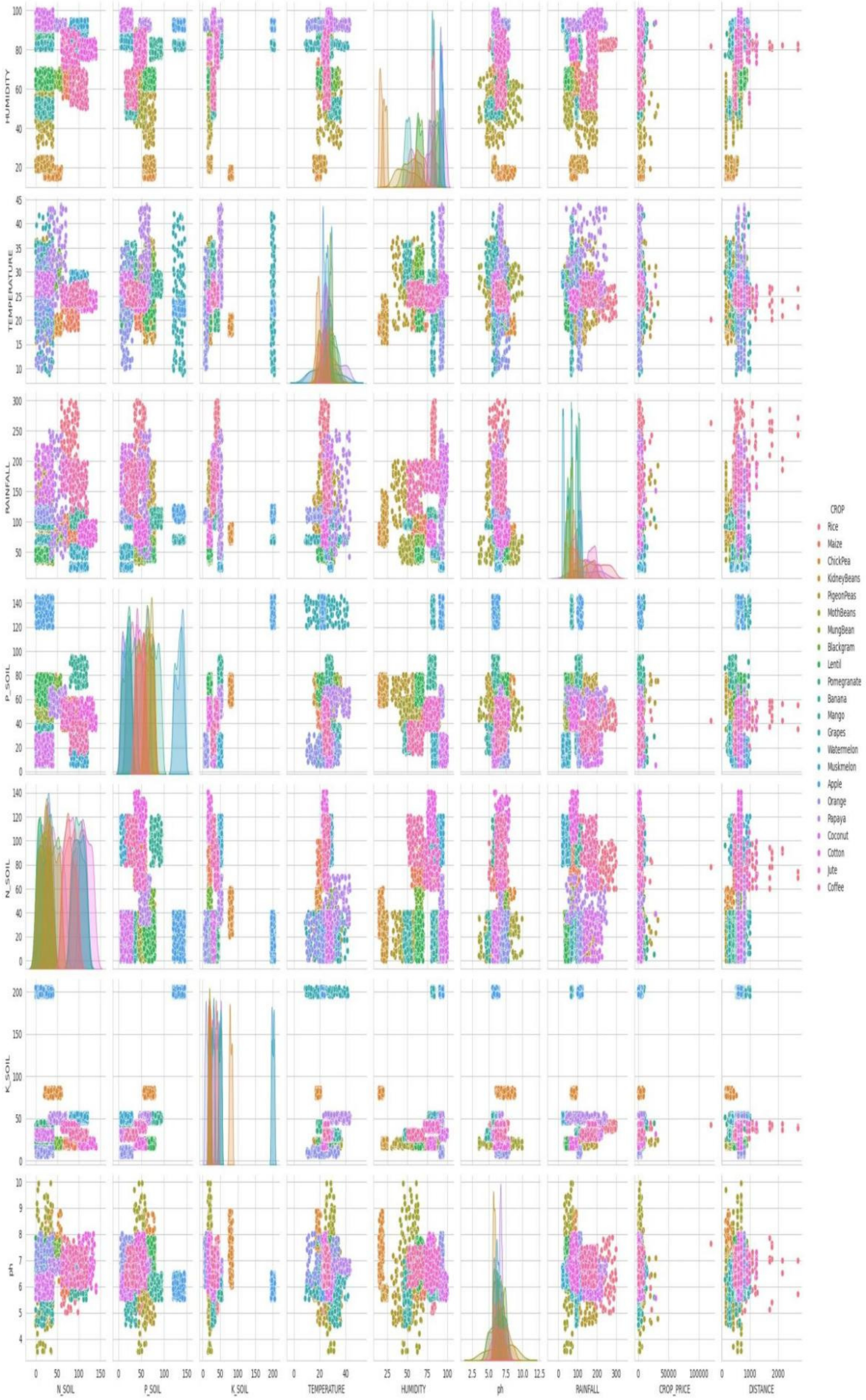

Figure 5. Crop Recommendation based on weather conditions and Soil Type.

‘HUMIDITY’, ‘TEMPERATURE’, ‘RAINFALL’, ‘P_SOIL’, ‘N_SOIL’, ‘K_SOIL’, ‘pH’ are the parameter values considered for plotting the graph.

As the results specify the range of the variable values that is being considered for the specific crop yield. This helps in analysis of knowing the highest value of specific variable needed for different respective crop types. As per the accuracy we can conclude that random forest considers all these parameters precisely and gives the output.

From Figure 5 visual representation of the results, we can infer the average range of a particular parameter value required for the good yield of the crops, which in return obtains greater profit in the market supply than usual As the crop price fluctuates accordingly.

From the Figure 5 results we can infer the predicted crops in specific state value are depicted in pair plot graph. the environmental variables ‘HUMIDITY’, ‘TEMPERATURE’, ’RAINFALL’, ‘P_SOIL’, ‘N_SOIL’, ‘K_SOIL’, ‘pH’ are considered.

The values represented are taken from the dataset which contains then approximate information of distance among the states and different combination of routes to attain the destination from the source state given in the input and the data of output from the machine learning or deep learning is being fed to obtain the optimal result.

In Figure 6 the obtained result is by implying the machine learning and deep learning algorithms performing comparative analysis of accuracy and practical implementation is being performed validating the obtained results.

As we can infer different states are in y-axis of the graph and the different type of crops present in the dataset are in the x-axis of the graph obtained along with the plot points depicting the results in different respective colors allotted to the crop.

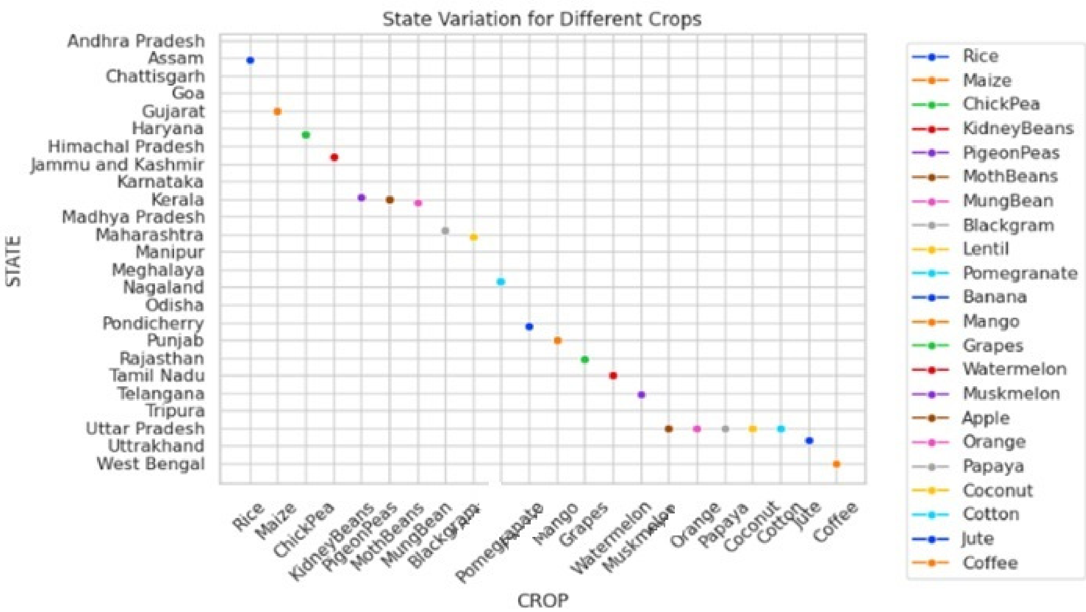

Figure 6. Crop Recommendation in specific states.

In Figures 7 and 8 we can visualize the parameters considered for route optimization implication by performing artificial algorithms such as ant colony artificial bee colony, simulated annealing. the parameters considered are the crop price and distance.

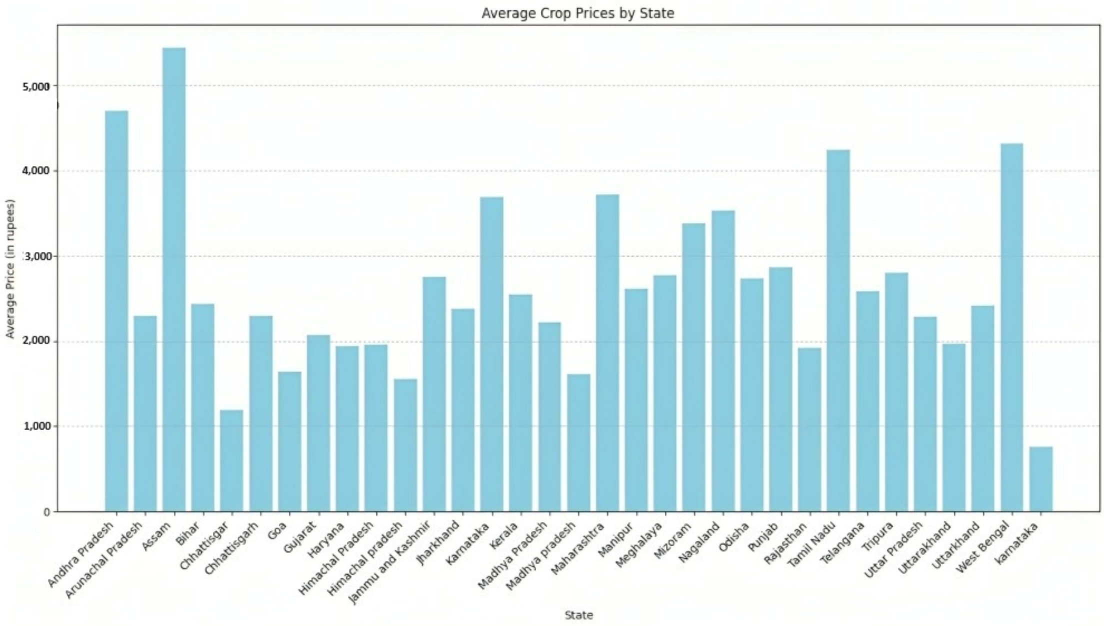

Figure 7. Visual representation of average crop prices with respect to different states.

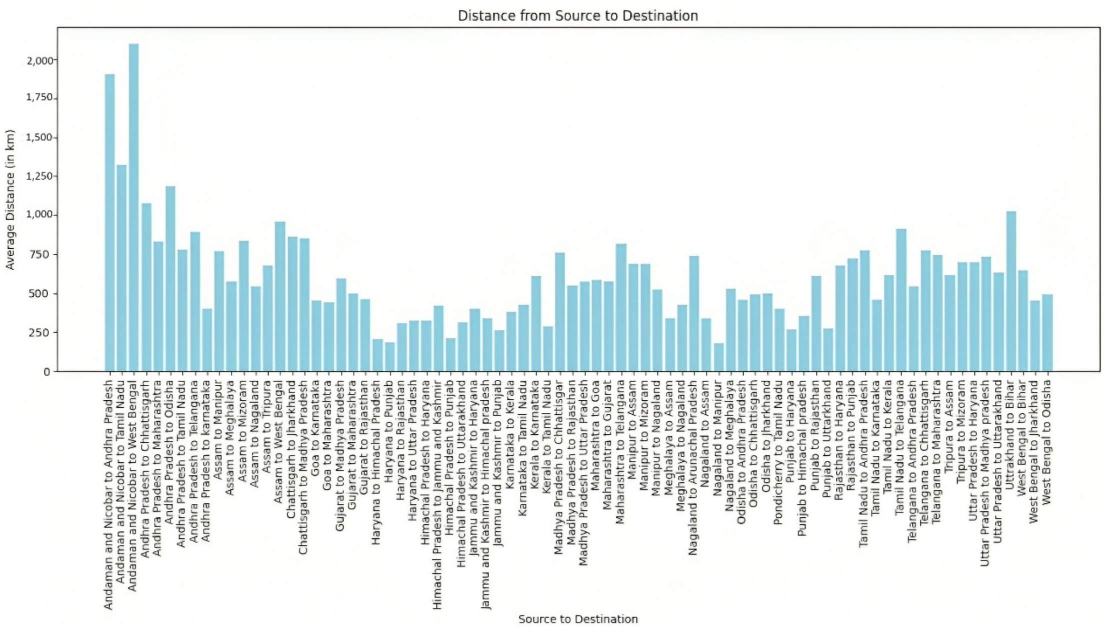

Figure 8. Average distance among states of crop supply.

The values represented are taken from the dataset which contains then approximate information of distance among the states and different combination of route information to attain the destination from the source state given in the input and the data of output from the machine learning or deep learning is being fed to obtain the optimal result.

In Figure 7 we can infer that the y-axis contains the average price value of the crops and x-axis contains the crop types the bar graph gives the visual representation of the result of average values.

In Figure 7 the result of average prices per state is depicted from which we can analyse which crop in yield gives the average highest crop price demand, likewise we can also obtain from the result regarding the least crop price average demanding state for the crop yield in that state.

In Figure 8. The average distance among the states of crop supply is depicted which helps in inferring the least and highest distance between the source state and the destination state.

The graphs obtained eases the analysis of least price and distance in and among the states to consider the parameter values for route optimization to be done by Artificial intelligence algorithms.

In Figures 9 shows the average temperature Variation for different crops plot graph is depicted.

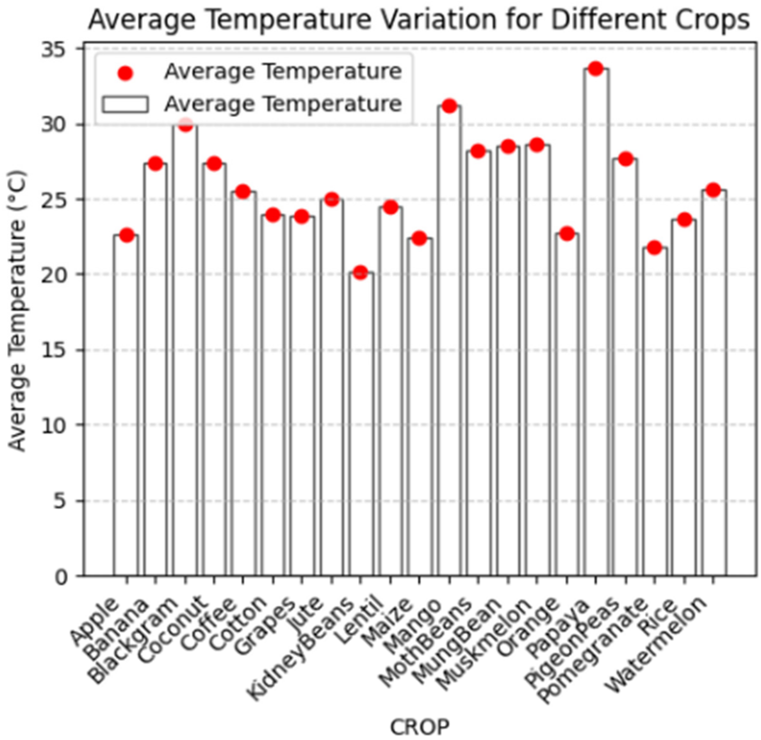

Figure 9 Average Temperature Variation for Different Crops.

The state and destination variation to analyse the producer resource and the consumer resource state by inter connecting the results obtained from the previous graphs of crop production and the state producing the crop.

These visualizations help us analyse the seasonal category does a particular crop belongs and the average temperature will conclude the basic need of a particular crop yield. This information helps the farmers and Supply chain management industry.

3.6.2. Result Analysis

Inferring from the given dataset, the integrated methodology of machine learning and artificial intelligence the crop prediction is done and optimal route as solution is obtained. From the Figure 5 results we can infer the average distance between the State and Destination and the result of the environmental variables that are considered SOURCE, DESTINATION, VIA1, VIA2, VIA3.

This section describes the model's experimental findings for figuring out the least expensive way to use the suggested algorithms to get to the best and most suitable path. Ant colonies, artificial bee colonies, and simulated annealing A comparative analysis has been conducted between the suggested algorithms and alternative algorithms based on factors such as application time, cost, time, availability, finding the best and most suitable path, and system efficiency.

A Python software that offers implementation to simulate and model the suggested system has been used to conduct the trials. The accuracy measures based on the ML model outcome pro- vides confidence on using the proposed approach.

The proposed work is successfully implemented as an intelligent assistant system in Supply chain management. The comparative analysis of the machine learning algorithms shown in Figure 10 signifies that Random Forest has the highest accuracy among the other algorithms and the second algorithm with maximum accuracy is LSTM algorithm of Deep learning is being performed integrating with artificial intelligence algorithms artificial bee colony, ant colony, simulated annealing.

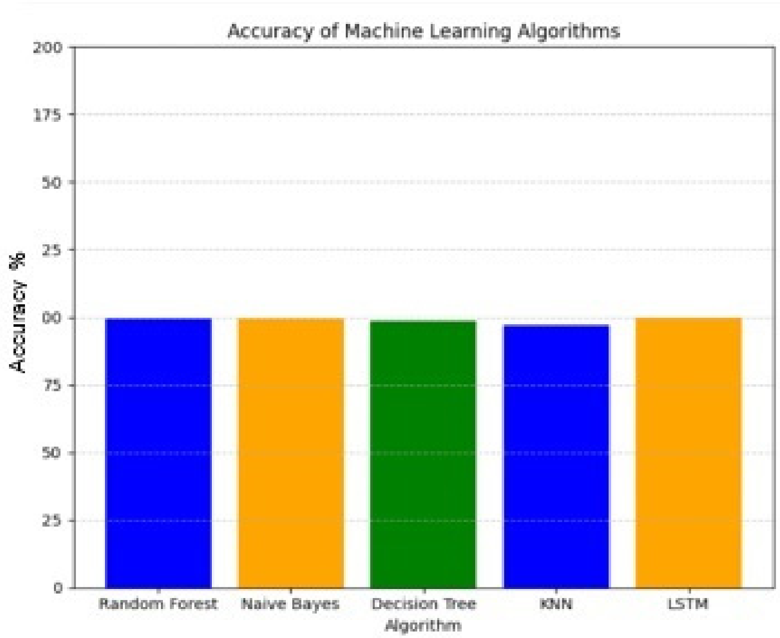

Figure 10 Accuracy value calculation for Validity of the proposed work.

4. Conclusions and Future Work

As transportation is a valuable key component in the Supply Chain Management sector to satisfy the customers with the quality and timely service, this project helps in validating the profit to the management as well as co-operates to the smooth function of the supply with efficient planning and implementation.

This research work has put forward the comparative analysis of the machine learning algorithms in the process of crop prediction and also considering deep learning algorithm as reference to compare the accuracy. The inference of the results state that the Random Forest Algorithm has the highest accuracy than the ither algorithms implied and equal to the same maximum accuracy deep learning algorithm LSTM also acquires the same maximum accuracy value.

The predicted crop obtained in the Random Forest algorithm is then fed to the Artificial algorithm where the optimization process considers the predicted crop as the base parameter and takes the input of the source state and then the artificial intelligence algorithms such as Ant colony optimization, Artificial bee colony optimization ,Simulated annealing are implied to calculate the optimal route by deciding the destination state to which the crop has to be supplied and then recommends the shortest route that can be reached with higher crop price demand in the m the market such that there will be profit as well as quality service satisfying the customers.

This research work has proposed a novel framework that combines the best features of Machine Learning Deep learning and artificial intelligence recommendation system for crops which is the real need in the supply chain management. The system is tested under various factors and using several test datasets. The results infer that, the put forward model of work is able to predict the crops with less time and also that provides optimal route solution. The system is dynamic in nature by providing the recommendations based on the parameters as given in the dataset.

Author Contributions

J.M.D.—Conceptualization, methodology, validation, formal analysis, investigation, resources, writing—review and editing, supervision, project administration, funding acquisition. M.V.—software, formal analysis, data curation, writing—original draft preparation. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

The data and supporting results will be provided on request due to privacy and confidentiality concerns.

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