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Surveillance and Predictive Information System for Tea Smallholdings (SPIS-TS)

[1]K.M.R.I. Senanayaka, [2]M.A.G. Jayawardena, [3]W.T.N.S. Piyarathna, [4]A.M.S.U. Abaymanna, [5]Sanvitha Kasthuriarachchi, [6]Koliya Pulasinghe

[1,2,3,4,5,6]Faculty of Computing, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka
Authors E-mail: [1]it20083700@my.sliit.lk, [2]it20130848@my.sliit.lk, [3]it20132446@my.sliit.lk, [4]it20127282@my.sliit.lk, [5]sanvitha.k@sliit.lk, [6]koliya.p@sliit.lk

***Abstract* - The purpose of this study is to solve the issues that tea smallholders experience in Sri Lanka's critical tea sector by introducing a complete Surveillance and Predictive Information System. Given that smallholder farmers are responsible for more than 75 percent of tea output while managing just 60 percent of tea land, it is clear that technologically driven solutions are required. In order to improve both productivity and income, the system integrates features such as disease diagnostics, cost prediction, yield optimization, and market forecasting. The system provides smallholders with actionable insights by utilizing cutting-edge techniques such as Convolutional Neural Networks (CNNs) for disease identification, Support Vector Machines (SVMs) for disease prevention, Autoregressive Integrated Moving Average (ARIMA) for cost prediction, Linear Regression for yield optimization, and Long Short-Term Memory (LSTM) for market forecasting. This method provides instruments for disease control, cost estimation, improved yield, and educated decision-making, all of which contribute to the expansion and continued viability of the tea business.**

Keywords: Tea leaf diseases, Deep learning, CNN, Machine learning, Productivity, Income enhancement, Yield optimization.

I. INTRODUCTION

Sri Lanka's exports and thousands of smallholders depend on tea. Tea growing, like other agricultural sectors, confronts several obstacles to sustainability and profitability. Foliar diseases, costs fluctuation, unexpected yields, and changeable market prices make tea smallholders' decision-making and resource allocation problematic [1]. A comprehensive Surveillance and Predictive Information System for Tea Smallholdings (SPIS-TS) is suggested to solve these issues. This research develops and integrates four important components of SPIS-TS to improve Sri Lanka's tea industry [2]. 1) Tea Foliar Disease Diagnosis and Control: Foliar diseases are one of the biggest dangers to tea farming. SPIS-TS's first component develops an accurate and reliable tea plant (Camellia sinensis) foliar disease detection system for prompt identification and targeted management. Blister Blight disease prediction using environmental data is difficult for farmers. The project also aims to create a prediction model using environmental data to anticipate Blister Blight occurrences for proactive disease management [3]. 2) Tea Cultivation Cost Prediction: Smallholding profitability depends on tea cultivation costs. SPIS-TS uses labor cost, fertilizer cost, weedicide cost, transportation cost to predict tea cultivation costs. Cost forecasts help smallholders maximize resource allocation, agricultural techniques, and economic sustainability [4]. 3) Predict the tea yield: Sri Lanka's many tea plant species make tea yield prediction difficult. SPIS-TS's yield prediction algorithm considers Sri Lankan tea plant cultivars' unique traits. The algorithm will anticipate tea yields by area using historical yield data, weather patterns, soil conditions, and agronomic methods, helping growers plan and manage their harvests [5]. 4) Forecasting Tea Demand and Market Price: Market dynamics strongly impact tea smallholding profitability. Farmers must forecast tea demand and pricing to plan output and marketing. SPIS-TS concludes with a forecasting model that uses historical market data, consumption patterns, and economic variables to predict Sri Lankan tea demand and market prices. Sri Lankan tea farmers can use the Surveillance and Predictive Information System for Tea Smallholdings (SPIS-TS) to make informed decisions and improve their tea cultivation practices. SPIS-TS seeks to change the tea business by controlling foliar diseases, estimating cultivation expenses, projecting tea yields, and predicting market trends.

II. RELATED WORKS

A) Integrated Pest Management and Disease Surveillance in Agricultural Systems

This discussion focuses on the methods of integrated pest management and disease monitoring measures, both of which are employed in an effort to reduce the negative effects of pests and diseases on agricultural products. It focuses on a holistic strategy that incorporates cultural, biological, and

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chemical strategies to successfully manage pests while simultaneously decreasing the dangers to the environment and to human health [6].

B) Decision-Support Systems for Smallholder Farming That Are Driven by Data

This discussion is on the creation of data-driven decision support systems that are specifically catered to the needs of smallholder farmers. These systems make use of agricultural data, such as the weather conditions, the quality of the soil, and trends in the market, to offer farmers actionable insights that can help them improve their planting, cultivation, and harvesting methods [7].

C) Using the Internet of Things to Conduct Environmental Monitoring in Order to Achieve Sustainable Agriculture

The technology known as the Internet of Things (IoT) is used to monitor and gather data on a variety of environmental parameters that might have an effect on agriculture. Some examples of these factors are temperature, humidity, soil moisture, and light intensity. This information is then used to make educated decisions on irrigation, fertilizer, and pest management, all of which contribute to farming techniques that are more environmentally friendly and productive [8].

D) Applications of Machine Learning for the Prediction and Control of Crop Disease

The evaluation of patterns in agricultural data is done with the use of algorithms that learn from machine data. This enables the prediction of crop diseases as well as the prospective epidemics caused by such diseases. Farmers are able to take preventative measures to lower the risk of disease and improve the overall health of their crops if they first identify the factors and patterns that lead to sickness. This allows the farmers to take preventative measures to minimize the risk of disease[9].

E) Decision-Support Systems for Smallholder Farming That Techniques for Precision Agriculture Utilizing Remote Sensing and Geographic Information Systems

In conjunction with Geographic Information Systems (GIS), remote sensing technologies such as satellite photography and drones provide accurate information on the properties of the land as well as the conditions of the crops. These technologies give farmers the ability to monitor the health of their crops, analyze the differences in the soil, and optimize the allocation of resources to achieve higher harvests [10].

F) Predictive Models for Agricultural Yield and Resource Management

Constructing predictive models that make use of both historical data and data collected in real time allows for increased accuracy in forecasting agricultural output. These models take into consideration a number of different aspects, including as the climate, the condition of the soil, and the sorts of crops that are being cultivated in order to guide choices on the distribution and management of resources. [11].

G) Predictions of the Agricultural Economy and Analysis of the Market

This field of research involves the application of economic. The use of models and the analysis of data in order to produce forecasts on market tendencies, the amount of demand, and price for agricultural commodities such as tea are both common practices. Farmers can benefit from having access to this type of information since it assists them in making informed decisions regarding the planting, harvesting, and marketing of their crops. [12].

H) Smart Farming Technologies for Enhancing Smallholder Productivity

Smallholder farms are increasingly making use of intelligent agricultural technology such as automation, sensor networks, and robots in an effort to improve their overall output. These technologies provide assistance with a variety of activities, including the scheduling of irrigation, the identification of pests, and real-time monitoring [13].

I) Climate-Resistant Farming Strategies for Tea Plantations

This field of study focuses on creating solutions that make tea farming more adaptable to shifting weather patterns because of the susceptibility of tea cultivation to climate change. [Given] the vulnerability of tea production to climate change. This might involve the utilization of climate-appropriate tea cultivars, the modification of planting schedules, and the improvement of watering procedures [14].

J) The Utilization of Information Systems in Agricultural Enterprises

An investigation of the use of information systems in agriculture, including agricultural software and mobile applications, as well as the acceptance of these technologies and their effects. This involves determining how the effectiveness of these platforms improves tea industry decision-making, communication, and efficiency [15].

K) Decision-Support Systems for Smallholder Farming That Integration of Technology with Sustainable Agriculture

Investigating ways in which environmentally responsible farming methods might be combined with contemporary

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agricultural technologies. This might incorporate practices like organic farming paired with technologies of precision agriculture for the development of tea that is more environmentally friendly [16].

L) Crop Disease Early Warning Systems Using AI

Using artificial intelligence to power systems that will examine a wide variety of data sources and deliver early alerts about potential crop diseases. Because of this, producers are able to take preventative steps or efforts to lessen the severity of the damage that diseases have on their tea harvests [17].

M) The Application of Big Data Analytics to Precision Farming

In order to achieve precision farming, processing and analyzing massive amounts of agricultural data using big data analytics is essential. Creating models that assist in maximizing the use of available resources, boosting productivity, and decreasing waste is required for this step [18].

III. METHODOLOGY

The research develops a Tea Smallholding Surveillance and Predictive Information System using data. Infected tea leaf photos are preprocessed and utilized to build a deep learning model for foliar disease identification, and a decision support module suggests control methods. Environmental data are preprocessed and utilized to build a machine learning model for Blister Blight disease prediction. A real-time monitoring system predicts Blister Blight infection, and a decision support module suggests prevention methods. A cost prediction model is trained, verified, and used to examine multiple cost scenarios to anticipate tea cultivation costs using historical labor cost, fertilizer cost, weedicide cost, transportation cost data. Tea yield prediction requires data collection on plant types, historical yields, and environmental variables, followed by model construction and customization for individual kinds. Forecasting tea demand and market prices requires time series analysis and forecasting models using past consumption and pricing data. Validation methods for each component evaluate all models' correctness.

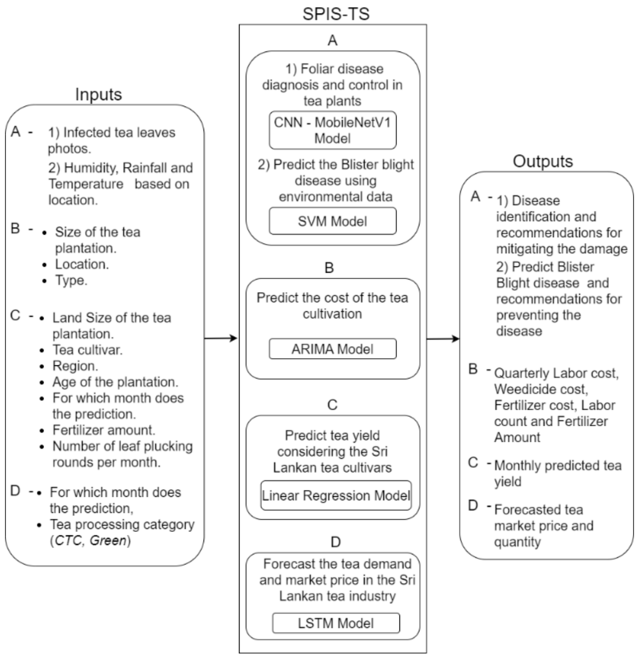

Figure 1: Overall System Diagram

Figure 1 displays the overall system diagram. The system has four main components, described below.

A) Foliar disease diagnosis and control in tea plants and predict the Blister blight disease using environmental data

- Image Dataset: A collection of labeled pictures of tea leaves, both healthy and sick, used to train the CNN model [19].
- Preprocessing: To get the photos ready for training, resize, normalize, and enhance them.
- Convolutional Neural Network (CNN) [19]: Use MobileNetV1 architecture for diseases diagnosis and tea leaf picture categorization.
- Disease Stage Identification: Educate a different CNN to recognize the stage of andiseases based on visual cues.
- Environmental Data: Gather environmental data (temperature, humidity, and rainfall) in real-time from a meteorological API.
- SVM: Support Vector Machine Using historical disease and environmental data, train an SVM model to forecast the occurrence of blister blight [20].
- Prediction and Recommendations: Based on SVM forecasts, provide predictions for the existence of the Blister Blight disease and suggest preventative actions.

The methodology is as follows: A thorough dataset of tea leaf photos is collected for the purpose of the disease diagnostic component. This dataset includes photographs of healthy as well as sick leaves, each of which represents a different foliar disease (such as Brown Blight, Blister Blight, Grey Blight, and Red Rust). This dataset has had some preliminary processing, which includes scaling, normalization,

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and augmentation. The dataset is then used to train a Convolutional Neural Network (CNN) model, more precisely the MobileNetV1 architecture. A high degree of accuracy is achieved as a result ofthe CNN's learning process, which involves the extraction of characteristics from the pictures and the subsequent classification of the images as either healthy or sick.

Methodologies for Making Predictions: The system uses a weather API to collect real-time environmental data such as rainfall, humidity, and temperature in order to make an accurate prediction of the incidence of the Blister Blight disease. There is a compilation of historical data on disease occurrences as well as environmental variables. In order to discover the correlations between environmental variables and disease outbreaks, a Support Vector Machine (SVM) model is trained on these data. The trained SVM model is able to provide predictions about the chance of the Blister Blight disease occurring whenever fresh environmental data is obtained. This enables proactive disease prevention planning.

B) Predict the cost of the tea cultivation

- Cost Dataset: Historical data compilation of labor expenses, weedicide costs, fertilizer costs, and land size.
- To prepare the dataset for analysis, clean, transform, and arrange it.
- Use the Autoregressive Integrated Moving Average (ARIMA) model for cost prediction and time-series analysis [19].
- Model Training: To identify patterns and trends, train the ARIMA model on the cost dataset [21].
- User inputs include: Obtain user inputs for cost calculation, such as size of the tea plantation (Acres), location (Ratnapura, Galle, Nuwara Eliya, Kalutara, Kandy), type (Bare land/Replanting).
- Cost Estimation: Forecast cultivation expenses depending on user inputs using the learned ARIMA model.

The methodology is as follows: The component of cost prediction starts with the development of a comprehensive dataset that includes historical information on numerous cost components that are involved in tea growing, such as labor expenses, weedicide prices, fertilizer costs, and land size. This information is then used to make cost predictions. This dataset is subjected to preprocessing, which entails both the cleaning and alteration of the data. When doing time-series analysis, an Autoregressive Integrated Moving Average (ARIMA) model is utilized for the purpose of identifying recurring themes and developing tendencies in the cost data. Because the ARIMA model is trained on the historical data, it is able to anticipate future cultivation costs depending on user inputs like location and land size. For example, the ARIMA model can predict how much it will cost to cultivate tea in the future.

C) Predict tea yield considering the Sri Lankan tea plant varieties

- Yield Dataset: Compilation of data on the type of tea grown, the area of the land, previous yields, the weather (rainfall, temperature, sunlight, etc.), and fertilizer use.
- To prepare the dataset for training, normalize, scale, and arrange it.
- Linear Regression Model: Apply linear regression techniques to increase yield [22].
- Data Splitting: For model training and validation, divide the dataset into training and testing sets.
- Model Training: To create links between input parameters and yield, train the linear regression model using training data.
- User inputs include: Obtain user inputs for characteristics such as land size of the tea plantation (Acres), tea cultivar (TRI2023, TRI2025, TRI2026, TRI2027, TRI4052, TRI4071, TRI3019), region (Nuwara Eliya, Kandy, Uva, Dambulla, UdaPussellawa, Sabaragamuwa, Ruhuna), Age of the plantation, for which month does the prediction, fertilizer amount, and number of leaf plucking rounds per month.
- To anticipate prospective returns based on user inputs, utilize the trained Linear Regression model.

The methodology is as follows: A dataset is generated in order to improve tea yield, with elements such as tea variety, land size, historical yield data, rainfall, temperature, sunlight, and fertilizer usage all being taken into consideration. A series of preparation steps, including normalization and feature scaling, are performed on the dataset. After that, the techniques for linear regression are utilized. The dataset is then separated into the training set and the testing set. The Linear Regression model is then trained on the training data to determine the correlations between the input parameters and the tea yield. The trained model is able to provide predictions about prospective yields depending on the inputs provided by the user, which assists smallholders in making decisions regarding farming.

D) Forecast the tea demand and market price in the Sri Lankan tea industry

- Gather historical information on market pricing and demand for tea.
- Data Preprocessing: Prepare the data for analysis by cleaning, handling missing values, and scaling.
- Long Short-Term Memory (LSTM) Models: Use LSTM models for forecasting and time-series analysis [23].

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- Model Training: To capture temporal patterns and trends, train LSTM models using historical data.
- User inputs include: The user picks the year for forecasting demand and market prices.
- Prediction: To predict tea demand and market prices for the given year, use trained LSTM models.
- Accuracy Metrics To evaluate the precision of forecasts, compute the mean absolute error and the mean squared error [24].

The methodology is as follows: The process of gathering historical data on the demand for tea and the price of the market contains the component of predicting. The data have undergone preliminary processing, which includes the management of missing values and scaling. Time-series analysis frequently makes use of models of the Long Short-Term Memory (LSTM), a kind of recurrent neural network (RNN) that was developed specifically for sequence prediction. For the purpose of identifying intricate temporal correlations and patterns, the LSTM models are given their training on the historical data. The results of these models are then utilized to make projections on future tea market pricing and demand. In order to ensure that the predictions provide accurate insights for decision-making, the accuracy of the forecasts is evaluated with metrics such as mean absolute error and mean squared error.

Each component of the Surveillance and Predictive Information System for Tea Smallholdings incorporates a systematic approach that spans data collection, preprocessing, model selection, training, and prediction. In other words, the system monitors and forecasts the performance of individual tea farms. The system equips smallholder farmers with useful tools for disease control, cost assessment, yield optimization, and market insights by merging cutting-edge approaches like as CNNs, SVM, ARIMA, and LSTM. This all-encompassing strategy bolsters the expansion and long-term viability of the tea business, while also providing smallholders with the tools they need to make educated decisions and improve their standard of living.

IV. RESULTS AND DISCUSSION

The "Results and Discussion" section summarizes the study's four components' results. The deep learning algorithm accurately predicted foliar disease incidences, enabling prompt treatments. A strong cost prediction model for tea cultivation provided accurate estimates for many situations. Variety-specific tea yield prediction algorithms showed accuracy variations, sparking talks on enhancing them. Although some discrepancies were identified, tea demand and market prices were largely expected to match actual patterns, highlighting the need for improved models and more data. The cross-component discussion highlighted how various components work together to help tea smallholders make educated decisions. Modeling assumptions and data availability were limitations. For an improved surveillance and prediction system, models, data sources, and future technologies may be refined.

A) Results

1) Foliar disease diagnosis and control in tea plants and predict the Blister blight disease using environmental data

a) Foliar disease diagnosis and control in tea plants

Figure 2: Tea foliar diseases images

Figure 2 displays sample images of tea foliar diseases. The dataset had been divided into four diseases: Blister Blight, Brown Blight, Red Rust, and Gray Blight.

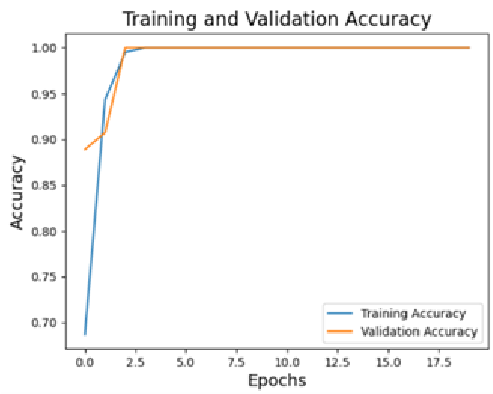

Figure 3: CNN - MobileNetV1 model training and validation accuracy level

Figure 3 displays the training and validation accuracy against 20 epochs of the tea foliar diseases identification model. According to the figure data, the MobilenetV1 model has 97.54% validation accuracy and 100% training accuracy for tea leaf disease identification. The results will be covered as disease identification and recommendations for mitigation diseases.

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b) Predict the Blister blight disease using environmental data.

The SVM model was trained using rainfall, humidity, temperature data and Blister Blight disease occurrence. The results will be covered as a prediction of Blister Blight disease occurrence and recommendations for the prevention of diseases.

2) Predict the cost of the tea cultivation

The results of the ARIMA model will be covered as a quarterly labor cost, weedicide cost, fertilizer cost, labor count and fertilizer amount.

3) Predict tea yield considering the Sri Lankan tea plant varieties

Figure 4 displays that the R2 score for training data is 7 and the R2 score for validation data is 6. A high R2 score indicates that a large amount of variability in the target variable (tea yield) can be explained by the model. This suggests that the predictions of the model are close to the actual values. The predicted results will be monthly tea yield.

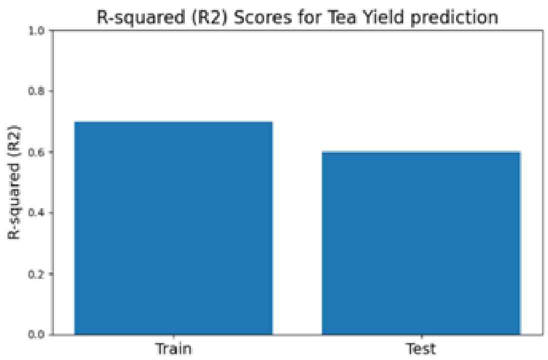

Figure 4: Linear regression model R-squared values for training and testing data

4) Forecast the tea demand and market price in the Sri Lankan tea industry

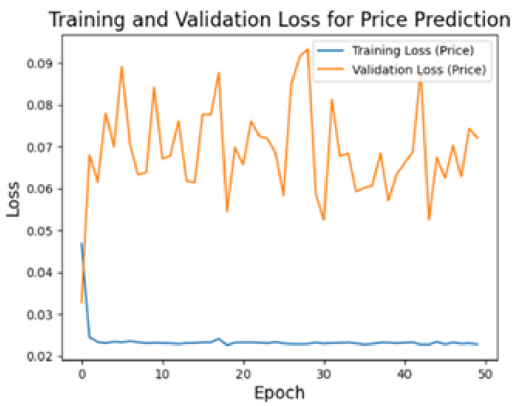

Figure 5: LSTM Model training and validation loss for price prediction

Figure 5 displays the training and validation loss against 50 epochs of the tea price prediction model. According to the figure data, the LSTM model has a validation loss lower than 0.1 and a training loss lower than 0.05 for tea market price prediction. The results will be demonstrated as forecasted tea market price.

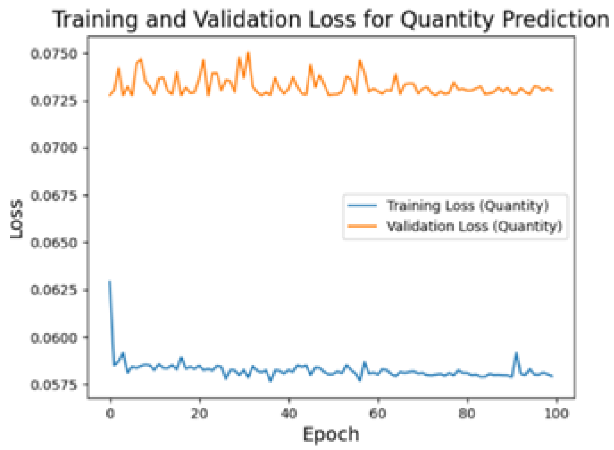

Figure 6: LSTM Model training and validation loss for quantity prediction

Figure 6 displays the training and validation loss against 100 epochs of the tea quantity prediction model. According to the figure data, the LSTM model has a validation loss lower than 0.08 and a training loss lower than 0.065 for tea market price prediction. The results will be covered as forecasted tea quantity.

B) Discussion

The study's ramifications are discussed in the "Discussion" section. The deep learning model for foliar disease diagnosis and control shows that early disease detection can result in timely actions that reduce crop losses. The cost prediction model's accuracy in anticipating cultivation expenditures shows it might help smallholder farmers allocate resources and manage budgets. Modeling varied development patterns is complicated by tea plant variety yield forecast accuracy. This complexity justifies more research into strengthening the algorithms to account for variety-specific traits to improve yield projections. The congruence of anticipated tea demand and market prices with actual patterns suggests the model might drive production and pricing choices. However, the observed differences highlight the need for constant model refining and additional data sources to improve predictions. The Surveillance and Predictive Information System's four research components' interconnection shows the integrated approach's ability to give tea smallholders with complete information. Data availability and model assumptions require continuing improvements. Future research may include model optimization, data stream

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augmentation, and technology investigation. The study's findings enhance tea cultivation and agricultural decision support systems.

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