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RESEARCH ARTICLE

Agricultural systems

Designing a closed-loop information flow model in bridging the market information gap among agriculture stakeholders in Sri Lanka

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Abstract: The stakeholders in the agriculture domain need agricultural information and relevant knowledge to make informed decisions at various stages of the crop life cycle. Coordination failures among the stakeholders in the agriculture sector result in the inability to provide accurate, timely, and actionable information. As a result, the agriculture sector faces several challenges, such as oversupply, undersupply and crop wastage. The existing digital agriculture eco-system can gather data produced by different stakeholders more frequently and accurately. However, the data collected from various stakeholders should be analyzed and forecasted to deliver the required knowledge to make more informed and appropriate decisions. This study was carried out to propose a 'Closed-loop information flow model' to provide forecasted demand and supply to create better coordination among stakeholders. Different prototypes were designed to deliver forecasted demand and supply information for major stakeholders in the agriculture sector. Initially, farmers, input suppliers, and logistic suppliers were selected in this study to expand to other stakeholders in the future. The prediction model was developed and evaluated according to stakeholder requirements by analyzing the actual and predicted data. The existing 'Govi-Nena' mobile-based farmer application was refined to provide supply and demand information for farmers. Separate web dashboards were designed to deliver the required information to other stakeholders such as input suppliers and logistic suppliers. Designed prototypes will be evaluated with the stakeholders for further improvements. The proposed Closed-loop information flow model for forecasted demand and supply will bridge the market information gap among stakeholders. Thus, it will reduce the coordination failures in the Sri Lankan agriculture sector while increasing transparency in making informed decisions.

Keywords: Closed-loop market information flow model, demand and supply modeling, UI/UX designing.

INTRODUCTION

Stakeholders involved in the agriculture domain need agricultural information and relevant knowledge to make informed decisions. Accurate agriculture information on market prices, seasonal weather, input supplies such as seeds, fertilizers, pesticides, machinery, and forecasted supply and demand are essential to make informed decisions at various stages of the crop production life cycle to achieve maximum potential productivity of each crop (De Silva *et al*., 2012; Sachin *et al*., 2020).

The current information flow within the agriculture domain resembles an open-loop system, creating difficulties in controlling information flow in the agriculture domain in Sri Lanka (Ginige, 2018). An open-loop information flow model is a control system where the system's output depends on the input. Still, the input or the controller is independent of the system's output. Hence, though the information is produced, there is no proper coordination among the stakeholders in an open-

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loop information system. As a result, stakeholders do not effectively access accurate and timely information; hence, they face several challenges. For example, at present, a common problem for Sri Lankan farmers is not being able to sell their harvest due to oversupply that occurs due to not getting the planned harvest and not being aware of market demand and supply in the planning stage (De Silva *et al.*, 2012; Ginige, 2018). Therefore, market demand and supply production predictions are essential for farmers and other stakeholders in the agriculture sector.

Developing a closed-loop information flow model to deliver accurate information and maintain better coordination among stakeholders is necessary for improving the agriculture domain in Sri Lanka. To that end, the 'Govi-Nena' project (www.govinena.lk) was initiated to create a digital knowledge agriculture eco-system to close up the open-loop information flow model for better coordination. The digital agriculture eco-system can gather data more frequently and accurately, combined with external sources (De Silva *et al*., 2014; Ginige *et al*., 2016). Data generated by the stakeholders can be further analyzed and forecasted to make more informed and appropriate decisions. The stakeholders can efficiently use this information with greater transparency and accuracy through a closed-loop (De Silva *et al*., 2012; Giovanni *et al*., 2013; Ginige, 2018) information flow model to produce actionable information.

Producing accurate information on agriculture market demand and supply is vital. Therefore, this study was carried out to propose a Closed-loop Information Flow Model (CIFM) to generate and deliver forecasted demand and supply information. The prototypes were designed to disseminate the information generated through the CIFM model among the main stakeholders in the agriculture domain.

The design of the CIFM model was influenced by the sustainable and closed-loop supply chain management research carried out in the literature. Over time, oversupply and undersupply may occur within the agriculture supply chain management due to inaccurate information on agriculture production. In addition, the lack of accurate information on service requirements, quantity, and quality of required services and products is another major cause within the agriculture supply chain (Mahaliyanaarachchi, 2003; Luthra, 2018; Sachin *et al*., 2020). Furthermore, in Sri Lanka, past studies have identified that oversupply and undersupply occurred in three major phases (Input supply stage, Production stage, Logistic supply stage) within the agriculture supply chain management (Basnayake, 2019; Sachin *et al*., 2020).

The concept of agriculture supply chain management is a relatively recent idea in agribusiness management literature that originated to reduce agriculture wastage in the agriculture product life cycle (Bhagat *et al*., 2011). However, the efficiency of such supply chain management systems can be increased by creating better networks and strong inter-relationships among all stakeholders, including input suppliers, producers, processors, traders, retailers, and consumers (Bhagat *et al*., 2011; Ackerman & Pantel, 2017).

Various types of opened-loop and closed-loop supply chain models have been proposed to manage the entire process of producing products and services in many different product manufacturing domains. The closed-loop supply chain concept is well defined for product manufacturing, where products are generally returnable after use (Amin *et al*., 2020). Closed-loop supply chain models have been used in such domains as a sustainable solution for preventing wastage while increasing productivity (Almató *et al*., 1999; Boin & Bertram, 2005; Barros *et al*., 2009; Abraham, 2011).

Returning used products is the significant difference between closed-loop and open-loop supply chain models (Ene & Öztürk, 2014; Ozceylan, 2016). The open-loop supply chain is a system whose constituent parts include material suppliers, production facilities, distribution services and customers linked together by the feed-forward flow of materials and feedback flow of information (Stevens, 1989; Ene & Öztürk, 2014; Ozceylan, 2016). However, in an open-loop supply chain, material or information does not flow back from the customer (Debo *et al*., 2004).

The existing agriculture supply chain models resemble open-loop supply chain models due to the nature of the products. Inefficiencies and product wastage are common factors if there is no proper coordination among the stakeholders within an open-loop supply chain (Cheraghalipour *et al*., 2018; Kamble *et al*., 2020). It is evident from other domains that introducing a closed-loop supply chain model can reduce the loopholes in an open-loop supply chain model (Cheraghalipour *et al*., 2018; Mosallanezhad, 2021). Such studies have shown that closed-loop supply chain models can effectively manage the domain stakeholders, thereby increasing efficiency and reducing wastage (Cheraghalipour *et al*., 2018; Zhao *et al*., 2018; Amirhossein *et al*., 2021).

Furthermore, studies conducted by Yuanjie (2017) and Zeballos (2014) stated the possibility of sharing the risk of uncertainty among the stakeholder within a closed-loop supply chain (Jabarzadeh *et al*., 2020; Salehi-Amiri *et al*., 2021). This can reduce the risk caused due to product uncertainty to a certain extent.

Designing a closed-loop supply chain model for the agriculture domain is a challenging task. Very few closed-loop supply chain models have been introduced in the agriculture domain. The research work carried out by Banasik and his colleagues (2017) demonstrated the possibility of designing a closed-loop supply chain in industrial mushroom production. They explored alternative recycling technologies to quantify trade-offs between economic and environmental indicators in mushroom production (Banasik *et al*., 2017). In addition, Cheraghalipour *et al.* (2018) proposed a Citrus closed-loop supply chain tool to minimize operational costs while maximizing responsiveness to customer demand. In this study, they have looked into the issue of spoiled fruits. Hence a returned product model was proposed to convert these into organic fertilizer and shipped as compost to customers (Iqbal, 2021). A similar study conducted by Mosallanezhad (2021) developed a mathematical tool to achieve cost savings in the seafood supply chain.

However, it is essential to identify different means and ways of designing closed-loop supply models other than the traditional concept in domains such as agriculture. We argue that by holistically providing and maintaining actionable information, an agriculture supply chain can be converted into a closed-loop scenario while reducing waste. There are hardly any modeling approaches in the literature on closed-loop agriculture supply chains using closed-loop information flow modeling concepts, particularly in the Sri Lankan context.

However, identifying and providing essential information is insufficient to achieve a sustainable closed-loop information flow model. A sustainable closed-loop information flow model should demonstrate continuous coordination, monitoring, analysis, and evaluation of the relevant information (Boulaalam *et al*., 2013, Yang, 2015; Zhou *et al*., 2018). With the rapid development of Information and Communication Technology (ICT), data and information can be effectively generated, stored, analyzed, and disseminated to support stakeholders in the agriculture sector. Thereby, this technology can be used to achieve a closed-loop information flow model to improve agricultural productivity and sustainability (Zhang *et al*, 2016).

In this regard, supply and demand predictions play an essential role in an agriculture supply chain for stakeholders to make informed decisions. Visibility of this type of actionable information will empower the farmers and other stakeholders in the agriculture domain to take suitable corrective measures on their production while minimizing oversupply or undersupply in the agriculture sector, thereby reducing waste. Therefore, a closed-loop information flow model was designed to disseminate the actionable information while balancing the demand and supply to ensure sustainability.

MATERIALS AND METHODS

This study mainly focuses on potato cultivation in Sri Lanka due to its high economic importance. Potato growers, the main stakeholder in the supply chain, face many issues and challenges. The main challenge is the lack of information and visibility of the supply and demand. However, not only the farmers but also the stakeholders within the supply chain, including Input suppliers, Logistic Suppliers, Exporters, and Policymakers (Struik, 2006; Ortiz *et al*., 2013; Beumer & Edelenbosch, 2019), even face issues due to the lack of information at the time of decision making. Hence, targeting the selected stakeholders in Sri Lankan potato cultivation, a closed-loop supply chain model was designed to increase visibility by providing real-time information to reduce wastage.

Design Science Research (DSR) methodology was used in this research study to design the proposed innovative artifact (model). As shown in Supplementary Figure 1, DSR consists of three major cycles (Hevner, 2007). The relevance cycle initiates DSR by providing the research requirements as inputs and defining acceptance criteria for the research results. Then the rigor cycle provides the existing knowledge to the research project to ensure its innovation. The design cycle refines the research activities and iterates more rapidly between the construction of an artifact, its evaluation, and subsequent feedback to further refine the design.

Major stakeholders involved in potato cultivation were identified through iterating the relevance cycle. As aforementioned, through surveys and existing literature, four major categories of stakeholders in the agriculture domain were identified: Farmers, Input Suppliers, Logistic Service Suppliers, and Policymakers. Exporters were excluded in the proposed model as no exports of raw potatoes were done to other countries (Agriculture and Environment Statistics Division, 2018).

The current demand and supply information requirements for each stakeholder to engage in the supply chain were further investigated via questionnaires and interviews. In addition, the current ways of obtaining predicted and real-time demand and supply information by the identified stakeholders to make decisions in providing services were also investigated. The studies revealed that predicted and real-time information was not shared adequately among these stakeholders. Moreover, they were making decisions based on rough measurements, and there was no proper coordination among the stakeholders to communicate this type of actionable information.

Farmers are not properly aware of the current production or market price to engage in potato cultivation. There were situations where overproduction or undersupply of potatoes is being reported in the market from time to time. On the other end, there were times when the government imported potatoes, creating an unprofitable marketplace for local potato farmers. To reduce this situation, farmers and the relevant stakeholders need information on the national consumption and the quantities of the production. Policymakers can also develop applicable policies in such circumstances to reduce the issues faced by the potato farmers.

The input suppliers provide seeds, fertilizer, pesticides, equipment, etc., that are locally produced or imported. Due to the difficulty in predicting the supply and demand, there were times when the input suppliers could not meet the demand and were defeated by their competitors. Almost all input suppliers currently predict the input requirement based on experience and informal measures.

The logistic service providers find it challenging to provide their services optimally due to the inability to predict the required services and quantities to be delivered. As a result, there were times when the product got wasted. Logistic suppliers can also save costs if they know the need beforehand and plan.

As per the findings, supply and demand information requirements for input suppliers, farmers (producers), and logistics suppliers are summarized in Table 1 below. Next, we iterated through the design cycle to design a CIFM to provide forecasted demand and supply to the relevant stakeholders. The proposed model was integrated with the existing 'Govi-Nena' mobile application. Based on the findings, the model was designed to cater to the supply and demand information needed at three levels: Farmer, Input Supplier, and Logistic Supplier.

The three main levels were considered in designing the proposed closed-loop information flow model to forecast stakeholders' demand and supply requirements based on the product quantities. The overall architecture of the proposed closed-loop information flow model is discussed in the next section.

The closed-loop information flow model (CIFM)

The closed-loop information flow architecture of CIFM model includes three (3) end-user levels and five (5) sub-modules to deliver the service requirement information required by the relevant stakeholders, as illustrated in Figure 1.

Table 1: Demand and supply information needs of the relevant stakeholders

Stakeholder	Information Needs
Farmers	Growing risk
	Market demand
	Market price
	Price predictions
	Price fluctuations
Input Suppliers	Predicted aggregated Input requirement for next year/season
	Predicted aggregated input requirement according to the District/ DS Division/ GN division / Agro-ecological Region.
	Crop production statistics
Logistic Suppliers	Predicted logistic requirement for next year/season
	Predicted aggregated logistic requirement according to the District/ DS Division/ GN division / Agro-ecological Region
	Crop production statistics

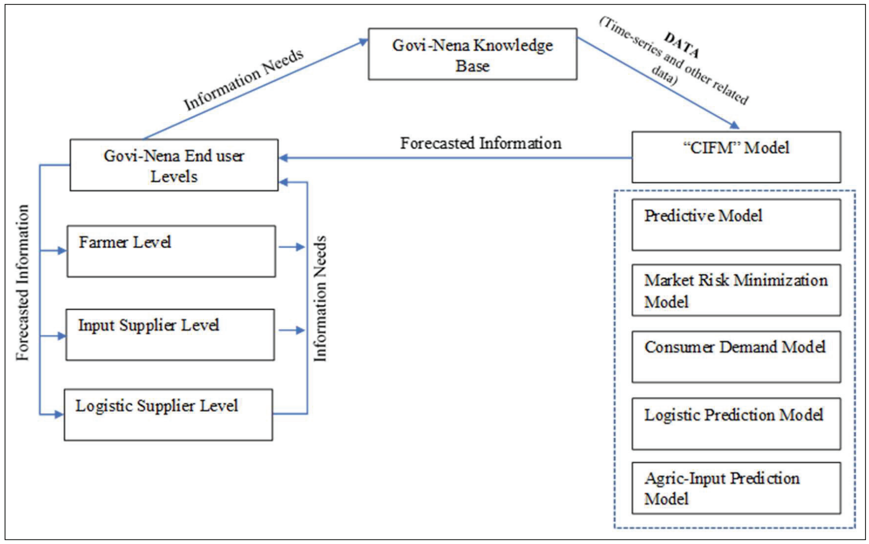

Figure 1: Closed-loop Information Flow Model (CIFM) architecture

Govi-Nena knowledge base

Govi nena Knowledgebase is containing two parts, one is crop ontology and the other one is a database that was developed to store market data which collects through users, and government domains. Through that database, CIFM model can get relavent data to forecast the market information.

Predictive model in CIFM

Crop forecasts are vital between the time of planting and harvesting. The past scholars used several techniques ranging from simple predictive techniques to advanced machine learning to predict crop yield. Forecasting methods can also vary from subjective to more objective ways. The subjective prediction methods are based on stakeholders' intentions or the forecaster's or other experts' opinions or intentions. The objective methods use a more statistical approach, including univariate to multivariate/associative techniques.

In crop yield prediction, different factors directly impact the accuracy of the forecast due to its dynamic nature. In that regard, the changing conditions concerning soil, weather, etc., play a significant role in predicting yield accurately. However, limitations in the availability of such data might cause considerable uncertainty in the large area yield forecasting models, especially when using multivariate/associative models (Russell & Van Gardingen, 1997; Hoogenboom, 2000). Hansen and Jones, (2000) revealed that it is unclear how these uncertainties transmit through the non-linear behavior of crop yield models and the aggregation errors that may creep in when aggregating crop yields to more significant regions. Moreover, several research studies were carried out to understand the effects of uncertainty in weather and other relevant factors on crop yield.

The crop yield modeling was focused on local-scale models to assess uncertainty in yield management (Bouman, 1994), condition of the soil (Launay & Guérif, 2003), and weather components that affect crop yield (Soltani *et al*., 2004; Fodor & Kovacs, 2005). However, the existing studies revealed that the accuracy was reduced primarily due to uncertainties in soil conditions and/or weather components. In addition, the local scale representation makes the results less representative of the regional-scale crop yield forecast.

Hence, in this study, we selected the district as a regional unit, i.e., forecasting crop yield over large areas to minimize the effect on prediction due to the unavailability or reliability of variables such as soil and weather conditions. Therefore, we used the univariate multi-step time series forecasting method based on the neural network in this study. In addition, the effect on variants was minimized by predicting specific selected districts/areas and seasons. Badulla and Nuwara Eliya districts were selected for this study because these are the major potato cultivating districts in Sri Lanka. In 2019. Potato harvest of 71759MT (3935Ha) and 28743MT (1422Ha), was produced in Badulla and Nuwara Eliya districts, respectively (Department of

Census and Statistics, 2019). According to past scholars, Multi-Layer Perceptron Neural Network (MLP), Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM) are used as multi-step univariate forecasting methods to make predictions (Ruß *et al*., 2008; Nevavuori *et al*., 2019; Schwalbert *et al*., 2020; Tedesco-Oliveira *et al*., 2020). Therefore, MLP, CNN, and LSTM techniques were used in this study. The measures of Mean Absolute Percentage Error (MAPE) and Normalized Root Mean Squared Error (NRMSE) were calculated and used in method comparison to select the best fit multi-step univariate forecasting method from the MLP, CNN, and LSTM neural networks. A time-series data set of the potato production for 1998–2019, covering both cultivation seasons, Yala and Maha, was obtained for Nuwara Eliya and Badulla districts from the Department of Census and Statistics to train and validate the univariate forecasting methods.

The predictive model in the proposed CIFM includes three (3) sub-processes. It uses real-time, time-series data generated due to the current usage of the 'Govi-Nena' mobile application. Supplementary Figure 2 illustrates the flow processes of the predictive model, and Table 2 lists the input, output, and outcome that will be fed at the next stage of the model.

Figure 2: Market information UIs in farmer app

Table 2: Data requirement of the predictive model flow processes

		Input	Output	Outcome
Predictive model	Step 1	The past seasonal growing land extent in Ha (area-wise)	Predicted area-wise growing land extent for next two seasons	Used in the Agric-Input prediction Model
	Step 2	The past seasonal harvest yield (area-wise)	Predicted area-wise harvested yield for next two seasons	Used in the Logistics prediction Model
	Step 3	Per capita consumption (area-wise)	Predicted per capita consumption (area-wise)	Used in the Consumer and Demand Prediction Model

According to table 2, area-wise growing land extent for next two seasons was forecasted using a selected multi-step univariate forecasting method using past seasonal growing extent (Ha). Then, the area-wise past seasonal harvest yield is used to predict area-wise harvested yield for the next two seasons with a selected multi-step univariate forecasting method. As the final step in the predictive model, area-wise per capita consumption was forecasted with the selected multi-step univariate forecasting method. Then the output was sent back to the Govinena knowledge base to be used as Inputs in the respective model mentioned under the Outcome in Table 2.

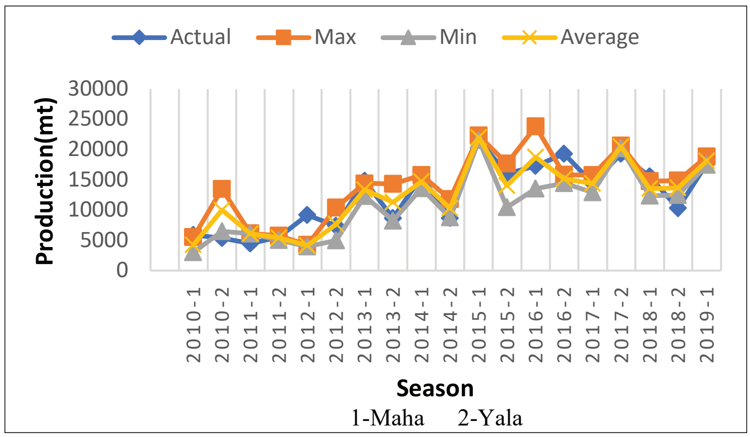

Figure 3: Maximum (max), minimum (min) and average seasonal potato production predicted by using LSTM neural network

Table 3: Consumer demand prediction model flow processes data requirements

		Input	Output	Outcome
Farmer market risk minimization model	Step 1	Predicted area wise harvested yield for next two seasons	Predicted area wise harvested yield for next two seasons	Used to make decisions in risk management
	Step 2	Real-time cultivation Ha (area wise) Average Yield per Ha	Average predicted yield per season	Used to identify market risk
	Step 3	The output of consumer demand prediction model Average predicted yield per season	Farmer's risk level (high/ moderate/good to grow)	Used to select the best crop to grow by minimizing the risk

Table 4: Farmer market risk minimization model flow processes data requirements

		Input	Output	Outcome
Farmer market risk minimization model	Step 1	Predicted area wise harvested yield for next two seasons	Predicted area wise harvested yield for next two seasons	Used to make decisions in risk management
	Step 2	Real-time cultivation Ha (area wise) Average Yield per Ha	Average predicted yield per season	Used to identify market risk
	Step 3	The output of consumer demand prediction model Average predicted yield per season	Farmer's risk level (high/ moderate/good to grow)	Used to select the best crop to grow by minimizing the risk

Consumer demand model in CIFM

The average consumption per person within a population is referred to as per capita consumption. Hence, predicted per capita consumption for the next two seasons, i.e., the output from the 'Predictive Model' and the area-wise average population, is used to calculate the area-wise consumption for the next two seasons. Table 3 shows the input, output, and model to which the output is fed at the next stage. Supplementary Figure 3 illustrates the flow processes of the Consumer Demand Prediction model. The output of this model was used as an input for the 'Risk Minimization Model' and the 'Logistic Prediction Model'.

Farmer market risk minimization model in CIFM

The main aim of this model is to provide actionable information six months before sowing seeds to assist farmers in minimizing the risk of oversupply or undersupply. First, the predicted area-wise harvested yield for the next two seasons is re-organized from the Predictive Model. Next, the derived information is provided to the farmer via the 'Govi-Nena' mobile application. Then, Real-time cultivation land extent (area wise) derived through the 'Govi-Nena' mobile application and the Average Yield per Hector, derived through the time series data, are used to predict the Average yield per season. Finally, the output derived from Step 2 and output derived from the Consumer Demand model indicate the market risk level, as illustrated in Table 4.

A color-coding mechanism is used to indicate the risk level based on predictions on the farmers' market risk level of the selected crop, as illustrated in Supplementary Figure 4. As such, the red color indicates the high market risk of growing the particular crop. Yellow color represents the 'Moderate' risk level, and hence farmers may opt for cultivating the relevant crop but with medium risk. The green color represents the 'Lowest' market risk level. The risk of producing the selected crop is minimal at that stage, and thus, farmers may choose to grow with minimum market risk.

Agric-input prediction model in CIFM

The two inputs for the 'Agric-Input Prediction Model' are the predicted area-wise growing land extent for the next two seasons and the average input (fertilizer & agrochemicals/ seeds/ machinery/ labour) requirement per Hector (Table 5). This calculates the input required for the next two seasons based on the input type. Supplementary Figure 5 illustrates the 'Agric-Input Prediction Model' flow processes for input suppliers.

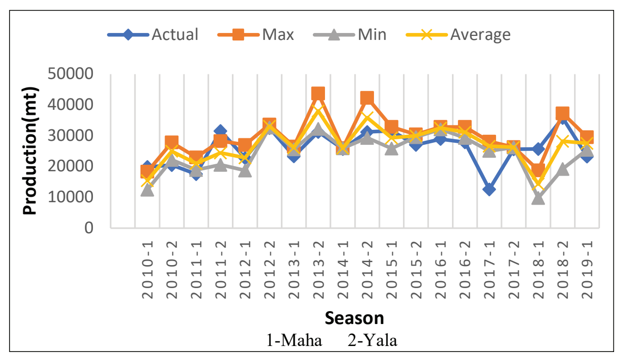

Figure 4: Maximum (max), minimum (min) and average seasonal potato production predicted by using LSTM neural network

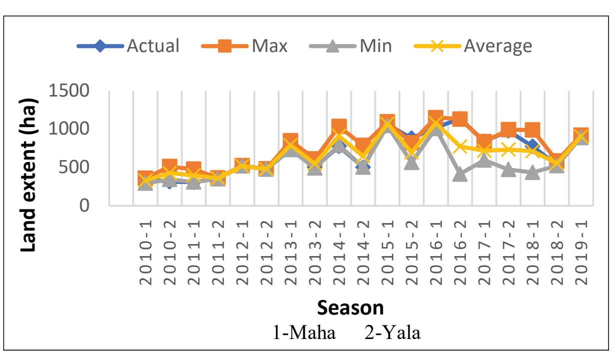

Figure 5: Maximum (max), minimum (min) and average seasonal potato cultivation extent predicted by using LSTM neural network

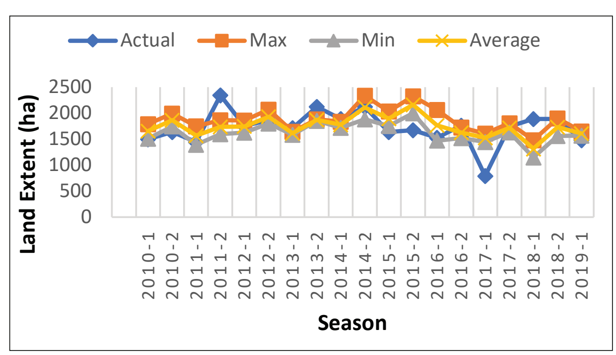

Figure 6: Maximum (max), minimum (min) and average seasonal potato cultivation extent predicted by using LSTM neural network

Logistic prediction model in CIFM

The 'Logistic Prediction Model' uses the output from the 'Consumer demand prediction model' and the predicted area-wise harvested yield for the next two seasons to predict the logistics requirement, as illustrated in Supplementary Figure 6. The logistic service providers require this information to plan and manage their services at their earliest and provide a better service for farmers. The derived data is re-organized to provide a better purview of the current trend. Table 6 lists the 'Logistic Prediction Model' flow processes data requirement.

Table 5: Data requirements for the input demand prediction model

	Input	Output	Outcome
Agric-Input prediction model	Predicted area-wise growing land extent for next two seasons	Predicted area-wise input requirement for the next two seasons	Used to plan and manage the agric-input requirements
	Input (fertilizer & agrochemicals/ seeds/ machinery/ labour) requirement per Ha		

Table 6: Data requirements for logistic demand prediction model

		Input	Output	Outcome
Logistic prediction model	Output Predictive Model	Predicted area wise harvested yield for next two seasons	Predicted area wise transport and storage requirement for next two seasons	Used to plan and manage the logistics requirement
		Output of consumer demand prediction model		

Designing the user interfaces

User Interfaces were designed to deliver the predicted outcomes on demand and supply derived from the proposed 'Closed-loop Information Flow Model,' iterating through the design cycle of DSR. In addition, the existing 'Govi-Nena' mobile farmer application was studied and refined to provide the predicted demand and supply information for farmers. The UI/UX design theories (Heimgärtner *et al*., 2017; Canziba 2018; Yu *et al*., 2020) were used to design the relevant interfaces.

Separate web dashboards were designed for other stakeholders, such as input suppliers and logistic suppliers, to deliver the required information through the 'Closed-loop Information Flow Model.' The designed prototypes will be evaluated with the stakeholders for further improvements.

Farmer mobile user interface: colour coding system for risk identification

The existing 'Govi-Nena' Farmer mobile application was refined to provide the predicted supply and demand information for farmers. When farmers are selecting the crops, awareness concerning the market risk is essential for better decision-making. The output derived from the predictive model was mapped to the proposed color schema (Giovanni *et al*., 2012) for the 'Govi-Nena' farmer application to minimize their market risk.

In the 'Govi-Nena' mobile application, as shown in Supplementary Figure 7 (a), farmers can go to the 'My Crops' section to add crops to their farms. In that stage, the farmers can see that the market risk will be highlighted using a color schema based on the results derived from the prediction model based on listed crops based. and the agro-ecological zones [Supplementary Figure 7 (b)],

The crops with a higher market saturation are denoted using red color. This color will inform the users that growing such crops may be risky due to the over-supply at the market level. The yellow color code was then used to show that the crop is in the intermediate level of market saturation; therefore, farmers can grow that crop at their own risk. The green color indicated that the crop had no market risk at that time. Therefore, farmers are encouraged to grow such crops to avoid crop wastage due to oversupply.

Moreover, the crop section in Supplementary Figure 7 (a) provides access to market information by clicking the market info icon to make an accurate decision during their cultivation. Looking at the color schema and these statistics, farmers can decide what to grow in which quantities and add the decided crops as they wish to the 'Short List' section [Supplementary Figure 7 (c)]. After farmers add their first selected crops to the shortlist, they can decide the growing extent and add the shortlist to the final grow list.

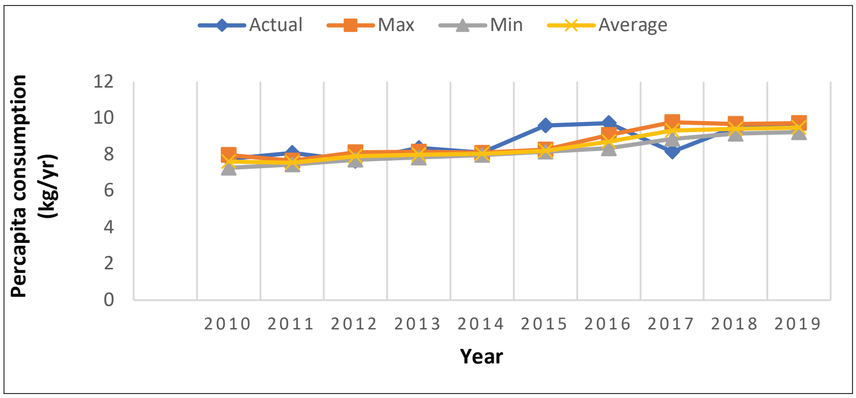

Figure 7: Maximum (max), minimum (min) and average per capita potato consumption predicted by using CNN neural network

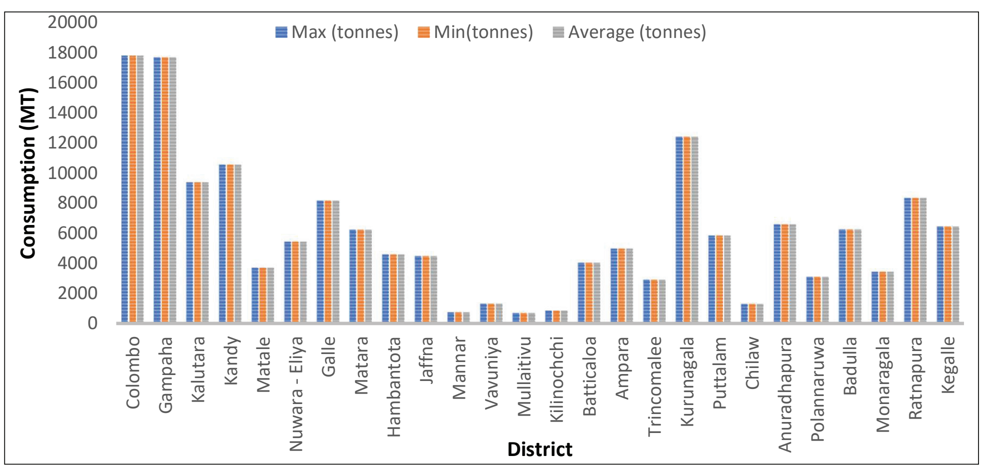

Figure 8: Maximum (max), minimum (min) and average area-wise potato consumption

Farmer mobile user interfaces: interface designs for delivering market information

Farmers can access the 'Market Info' section to get an idea about all available crops grown in their area [Figure 2(a)]. The 'market info' section will allow farmers to access market information related to the selected crops. For example, when a farmer chooses a crop, a farmer can view the predicted crop cultivation statistics per season. In addition, monthly and seasonal price changes will be shown to the user, as illustrated in Figure 2 (b, c, and d).

Input supplier user interfaces: interface designs of the input suppliers dashboard

The prototype design of the input suppliers' dashboard is designed to visualize information on area-wise input requirements for crop cultivation, expected growing extent, and expected production for the next season. As shown in Supplementary Figure 8(a), the 'Market Summary' tab on the home page summarizes the current crop extent grown by the farmers. Moreover, users can get access to the input requirements details directly by clicking the 'icons' (Seeds & seedlings, Agrochemicals, Agromachinery, and Labours) in the 'input requirement' section, as shown in Supplementary Figure 8 (a). Users can select the crop in the input requirement section to view the predicted or real-time input requirement data.

Moreover, users can access the predicted crop data for the next two seasons by clicking on each crop's predicted tab, as shown in Supplementary Figure 8 (b). After accessing the predicted section [Supplementary Figure 8 (c)], users can select the district to obtain aggregated predicted input requirements for the next two seasons. In addition, users can obtain information on predicted growth extent and yield according to the selected area. Moreover, users can also access real-time input requirements by clicking the 'real-time' tab in each crop [Supplementary Figure 8 (b)]. Thereafter, farmers can access the real-time information interface, as shown in Supplementary Figure 8 (d). According to Supplementary Figure 8 (d), users can select the district to get aggregated real-time information. After selecting the district, users will gain the ability to access real-time seasonal input requirements. Moreover, users also can get information about real-time changes in the growing extent and real-time production [Supplementary Figure 8 (d)].

Logistic supplier user interface: interface designs of the logistic suppliers dashboard

As illustrated in Supplementary Figure 9, the prototype was designed to deliver area-wise seasonal requirements on farmers' harvested yield's transport and storage needs. During the field interviews, the logistic suppliers informed that they need next season's expected growing extent and expected production to better coordinate and manage their activities. Hence, to fulfill this requirement, expected national real-time growing extent and expected production statistics are added to their dashboard.

In addition, the logistic suppliers can access the predicted and real-time logistic requirements by clicking the 'predicted' or 'real-time' tab in each crop, as shown in Supplementary Figure 9 (a). After accessing the predicted section, users must select the district to obtain logistic information, as shown in Supplementary Figure 9 (b). After that, users can access transport and storage requirements according to the selected district for the next two seasons. Moreover, in this section, users also can get information about the predicted growth extent and production according to the district chosen for the next two seasons.

Furthermore, users can access the Real-time information by clicking the 'Real-time' tab in the 'Logistic Requirement Section,' as shown in Supplementary Figure 9 (a). After accessing the Real-time section, users need to select a district in which they are willing to get Real-time logistic information [Supplementary Figure 9 (b)]. Thereafter, users can get information on Real-time transport and logistic requirement according to the selected district. In addition, users can access the information on real-time changes in growing extent and production according to the chosen area, as shown in Supplementary Figure 9 (b).

RESULTS AND DISCUSSION

Predictive model

The predictive model was trained for potato cultivation based on the derived dataset.

Predictions of area-wise potato production

Three models were developed by using MLP, CNN, and LSTM. The models were trained and validated using the data from the Nuwara Eliya district's seasonal potato production. Maximum, minimum, and average seasonal potato production was predicted through MLP and CNN models for the Nuwara Eliya district, which are shown in Supplementary Figures 10, 11, and the LSTM model in Figure 3. The expected production results were analyzed against the actual seasonal potato production.

The model developed using MLP showed the highest (23.21%) mean absolute percentage of error compared to the CNN (23.08%) and the LSTM (19.68%). However, when considering the NRMSE, MLP showed a lower (0.226) value than the CNN model (0.229). The LSTM model has shown the lowest NRMSE value of 0.118 among all three models (Supplementary Table 1).

All pre-trained MLP, CNN, and LSTM neural network models for Nuwara Eliya were fine-tuned to make the potato production predictions for Badulla District. The models were compared using the NRMSE and MAPE. Actual seasonal potato production and predicted maximum, minimum, and average seasonal potato production using MLP and CNN models for the Badulla district were illustrated in Supplementary Figures 12 and 13 and the LSTM model in Figure 4.

Comparing the forecast accuracy by using the measures mentioned in Supplementary Table 2, CNN showed the highest (22.82%) mean absolute percentage of error (MAPE) when compared to the MLP (20.50%) and the LSTM (19.87%). Moreover, when considering NRMSE, CNN has shown a higher NRMSE (0.248) value than MLP (0.243). However, LSTM has demonstrated the lowest NRMSE value of 0.219 among the models. Therefore, the LSTM model showing high accuracy level than other methods. LSTM was used to predict seasonal potato production, and the results are shown in Supplementary Table 3.

Prediction of the area-wise land extent of potato cultivation

The same procedure mentioned above was carried out to predict the land extent for potato cultivation in Nuwara Eliya and Badulla District. Maximum, minimum, and average seasonal potato cultivation land extent were predicted through MLP and CNN models for Nuwara Eliya district as shown in Supplementary Figures 14, 15 and LSTM models in Figure 5. The predicted seasonal potato cultivation land extent was analyzed against the actual seasonal potato cultivation land extent.

The MLP showed the highest (19.40%) mean absolute percentage of error compared to the CNN (17.96%%) and the LSTM (13.11%). However, when considering the NRMSE, MLP showed a higher (0.265) value than the CNN model (0.201). On the other hand, the LSTM model has shown the lowest NRMSE value of 0.188 among all three models (Supplementary Table 4).

Pre-trained MLP, CNN, and LSTM models for the Nuwara Eliya dataset were fine-tuned to make the potato production predictions for Badulla District. The models were compared by using the NRMSE and MAPE. Actual seasonal potato cultivation land extent and predicted maximum, minimum and average seasonal potato cultivation land extent results of MLP and CNN models for the Badulla district were illustrated in Supplementary Figures 16, 17, and LSTM model in Figure 6.

As a result, the CNN has shown the highest (20.04%) mean absolute percentage of error (MAPE) when compared to the MLP (17.37%) and the LSTM (15.62%). Moreover, when considering NRMSE, the CNN showed a higher NRMSE (0.231) value than MLP (0.206). However, the model developed using LSTM showed the lowest NRMSE value of 0.180 compared to other models (Supplementary Table 5). Therefore, LSTM was used to predict the land extent of seasonal potato production, and the results are shown in Supplementary Table 6.

Prediction of per capita potato consumption

Maximum, minimum, and average national per capita potato consumption was predicted using MLP and CNN models for Nuwara Eliya district as shown in Supplementary Figures 18, 19, and LSTM model in Figure 7. The predicted national per capita potato consumption results were analyzed against the actual national per capita potato consumption, as illustrated in the graphs.

Comparing forecasting models, the LSTM showed the highest (3.93%) mean absolute percentage of error compared to the MLP (3.60%%) and the CNN (3.10%). However, when considering the NRMSE, LSTM showed a higher (0.105) value than MLP (0.094). On the other hand, CNN has shown the lowest NRMSE value of 0.090 compared to other models (Supplementary Table 7). Hence, CNN was used to predict the per capita potato consumption and the results derived are listed in Supplementary Table 8.

Consumer demand prediction model

The output from the 'Predictive Model' and the national average population were used to calculate predicted per capita consumption for the next two seasons, and it is illustrated in Supplementary Figure 20. The area-wise average population was used to calculate the area-wise potato consumption as illustrated in Figure 8.

Agric-input model

Prediction of area wise fertilizer requirement

The predicted seasonal potato cultivation land extent and the average fertilizer requirement per hectare were used to predict the area-wise potato fertilizer requirement. Urea, Triple Super Phosphate (TSP), and Muriate of Potash (MOP) are the three major potato fertilizers used in potato cultivation. The fertilizer usage requirement of Urea, TSP, and MOP for the Nuwara Eliya district were illustrated in Supplementary Figures 21, 22, and 23, respectively. Similarly, the Badulla district's Urea, TSP, and MOP requirement fertilizer requirement were calculated and depicted in Supplementary Figures 21, 22 and 23, respectively.

Prediction of area-wise seed potato requirement

The seed potato requirement was calculated using the predicted seasonal potato cultivation land extent and average seed potato requirement per hectare. The estimated seasonal seed potato requirement for Nuwara Eliya and Badulla district was graphed in Supplementary Figures 24 and 25.

Prediction of area-wise labour requirement

The predicted land extent of the seasonal potato cultivation and the required number of labor hours per hectare were used to calculate the average number of labor hours needed for potato cultivation. Supplementary Figures 26 and 27 depict the labor requirement for Nuwara Eliya and Badulla districts, respectively.

Logistic model

The output from the consumer demand prediction model and the predicted area-wise harvested yield for the next two seasons was used in the 'Logistic Model' to provide re-organized predicted logistic requirements. Supplementary Table 9 shows the expected potato production in metric tons (MT) in different districts in Sri Lanka, while Supplementary Table 10 represents the area-wise potato consumption. Having this information beforehand in an organized manner, the logistic suppliers can plan and effectively manage their services.

Discussion

The study concludes that the proposed 'Closed-loop information flow model' for providing the forecasted demand and supply information for stakeholders will reduce wastage while bridging the information gap. The proposed model will reduce coordination failures and increase transparency among the stakeholders in the agriculture sector of Sri Lanka. The existing 'Govi-Nena' mobile farmer application was refined and improved to provide supply and demand information for farmers. Separate web dashboards designed for other stakeholders, such as input and logistic suppliers, will deliver the required information more effectively and efficiently.

Comparing MLP, CNN, and LSTM multi-step univariate forecasting methods, the LSTM method shows the lowest value of mean absolute percentage error and normalized root mean square error than CNN and MLP method. Therefore, the LSTM multi-step univariate forecasting method can forecast demand and supply values.

CONCLUSION

The stakeholders in the agriculture domain need agricultural information and relevant knowledge to make informed decisions at various stages of the crop life cycle. However, coordination failures among the stakeholders in the agriculture sector result in the inability to provide accurate, timely, and actionable information. As a result, the agriculture sector faces several challenges, such as oversupply, undersupply and crop wastage. According to the preliminary surveys, the stakeholders mentioned the possibility of minimizing the over-supply to reduce waste and minimize the undersupply situations at the market level if they have access to supply and demand data beforehand. Moreover, managing coordination to reduce waste is essential for an agriculture supply chain. We have designed a closed-loop supply chain model to reduce waste by providing supply and demand information for relevant stakeholders. Many product manufacturing organizations argue that closed-loop supply chain models can be used to coordinate the supply chain better, reducing waste. However, the same cannot be applied to manage agriculture supply chains due to the nature of the products and the dynamic nature of the information shared by the stakeholders. To that end, the proposed model resembles a closed-loop information flow model for the agriculture supply chain.

The closed-loop information flow model receives user inputs, feedback, suggestions, and requirements through the 'Govi-Nena' mobile application. The CIFM derives real-time and past time-series data from the 'Govi-Nena' Knowledgebase to make necessary predictions required by the proposed prediction models. The predicted data will be sent back to the 'Govi-Nena' Knowledgebase for further processing. The processed data will be distributed to the corresponding end-users through the designed user interfaces based on their need.

In return, user actions will be restored in the 'Govi-Nena' Knowledgebase for further processing (Supplementary Figure 28). The proposed model will only provide information for the stakeholders to make their own decisions. The accuracy level of the proposed model will be provided, and hence it will aid the stakeholders when making their decisions at minimum risk. Though the usability of the proposed user interfaces was evaluated during the initial field studies, complete validation of the proposed model is yet to be carried out. The accuracy of the proposed model was limited due to the lack of available data for predictions. However, we claim that the required data for predictions will be available when users start using the model through the 'Govi-Nena' mobile app. The challenge faced in designing the proposed solution due to the lack of technology awareness among the stakeholders was achieved through designing user-friendly interfaces. Based on the user survey, it was evident that most stakeholders were willing to use this digital agricultural model to fulfill their information needs.

Future work

The designed prototypes will be evaluated further using the stakeholders for further improvements.

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