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Research Article

Cultivation Planning across Europe using Machine Learning Techniques

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Abstract

Due to their limited accessibility to the soil information and price prediction information of the agricultural products, farmers grow their crops based on the common practice in their regions. This leads to non-sustainability in agriculture and imbalance between farmers' production and customers' demand, respectively. To address the above-mentioned issues, we propose an ICT-based cultivation planning policy and system, named AgriTrade. The basic operation of AgriTrade lies in, first, incenting farmers to participate in the cultivation planning in an interactive manner using a mobile app, second, employing machine learning algorithms to provide high precision price and soil information for farmers using data collected from across the supply chain. To demonstrate the feasibility of AgriTrade, we carry out a pilot use case by collecting the last 15 years' tomato prices of Europe and the statistics of tomato cultivation of farmers in Turkey, which is one of the biggest tomato exporters of the EU. AgriTrade forecasts the future tomato prices based on the historical tomato prices of the EU. We compare the traditional way marketing and forecast-based marketing of tomatoes: While the traditional way marketing is to immediately sell the product when it is grown, the forecast-based marketing is to store the product until the time the product's prices is higher based on the predicted prices and to sell it. The results show that when the farmers of Turkey apply the forecast-based marketing, they can remarkably increase their profits around 9.1% compared with the traditional way marketing.

Keywords: Smart Farming, Agrifood Chain, Machine Learning, Price Forecast.

Makine Öğrenmesi Tabanlı Tüm Avrupa için Tarımsal Ekim Planlaması

Öz

Tarımsal ürünlerin toprak bilgisine ve fiyat tahmin bilgilerine sınırlı erişimleri nedeniyle, çiftçiler mahsullerini bölgelerindeki ortak uygulamaya göre yetiştirmektedir. Bu, tarımda sürdürülebilirliğin devam ettirilememesine ve çiftçilerin üretimi ile tüketicinin talepleri arasında bir dengesizliğe yol açmaktadır. Yukarıda belirtilen sorunları ele almak için AgriTrade adlı BİT (ICT) tabanlı bir tarımsal ürün yetiştirme planlama politikası ve sistemi öneriyoruz. AgriTrade'in temel operasyonu, öncelikle çiftçileri bir mobil uygulama kullanarak interaktif bir şekilde ekim planlamasına katılmaya teşvik etmek, ikincisi, tedarik zincirinden toplanan verileri kullanarak çiftçilere yüksek hassasiyetli fiyat ve toprak bilgisi sağlamak için makine öğrenimi algoritmalarını kullanmaktır. AgriTrade'in fizibilitesini göstermek için, Avrupa'nın son 15 yıllık domates fiyatlarını ve AB'nin en büyük domates ihracatçılarından biri olan Türkiye'deki çiftçilerin domates yetiştiriciliği istatistiklerini toplayarak bir pilot kullanım örneği gerçekleştiriyoruz. AgriTrade, AB'nin tarihi domates fiyatlarına dayalı olarak gelecekteki domates fiyatlarını tahmin ediyor. Domatesi geleneksel yöntemle pazarlamayı ve tahmine dayalı pazarlamayı karşılaştırıyoruz: Geleneksel pazarlama yöntemi, ürünü yetiştirildiğinde hemen satmak iken, tahmine dayalı pazarlama, ürünü, ürünün fiyatlarının daha yüksek olduğu tahmin edilen ana kadar depolamaktır. Sonuçlar, Türkiye'deki çiftçilerin tahmine dayalı pazarlamayı uyguladıklarında, geleneksel yolla pazarlamaya kıyasla karlarını % 9,1 civarında önemli ölçüde artırabileceklerini gösteriyor.

Anahtar Kelimeler: Akıllı Tarım, Makine Öğrenmesi, Tarımsal Gıda Zinciri, Fiyat Tahmin.

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1. Introduction

The difference between demand and supply of agricultural products in the EU causes financial loss for both farmers and consumers. In particular, without considering the effect of dynamicity of agricultural markets (local and global), growing agricultural products with only farmers' foresight leads to an imbalance between food demand and supply. To address this issue, existing Market Information Systems (MISs), collecting, processing, and disseminating information on the agricultural markets, must be enhanced by feeding online data acquired across the supply chain (from farmers to consumers) to offer more intelligent recommendations to farmers (Deichmann et al. 2019; Aker & Fafchamps, 2015).

Moreover, growing unsuitable agricultural products in the farms causes a decrease of product quality and soil fertility. Since the nutrient content of soils changes over time, to maintain the fertility and product quality, changing the product grown over time is of great importance. To get the highest yield and ensure sustainable farming, building a Soil Information System (SIS) (enriched interacting with farmers), containing comprehensive soil tests data, water, wind, sunshine, and precipitation data for each area, is an essential task (Tayyebi et al. 2016; Wolfert et al. 2017; Seyedmohammadi et al. 2018).

The above-mentioned MIS and SIS systems' usage by farmers and their effects on farms and farmers' income, despite the proposed enhancements, might be very limited. The reason of this issue is the lack of 1) an appropriate media providing an interactive communication platform between farmers and the systems, and 2) incentives that direct farmers toward the recommendations (Aker & Fafchamps, 2015; Antonopoulou et al. 2010).

To address this issue, we propose an ICT-based cultivation planning system, named AgriTrade, which exploits the incentives (fundings of the EU and national governments to support farmers) to direct the farmers to grow the recommended products in the cultivation plan. The recommended products list for each farm is delivered to farmers using a mobile app, also enabling farmers to respond to the offers. By doing so, AgriTrade is able to direct farmers to suitable products in addition to knowing what farmers will grow. The cultivation plan is performed according to the data provided from the enhanced MIS and SIS systems by employing machine learning (ML)-based algorithms, supervised by a training data provided by financial, agricultural field experts. The ML-based algorithms deal with dynamicity of the data of the MIS, and estimates the missing information about the farms from existing data of the other farms in the SIS. Furthermore, the developed ML-based forecast algorithm allows farmers to predict the future prices of their products. According to the forecasted prices, farmers can store and then sell when the time the price is higher, which enable the farmers to increase their incomes.

Contributions in the case of usage of AgriTrade for the EU and its partners: 1) the farmer can select right products to grow, considering the whole picture, not only the EU but also the global agricultural markets. 2) farmers can improve their incomes exploiting the forecasted prices 3) sustainable farming can be easily stimulated 4) the incentives of the EU and local governments are effectively managed. and 5) the consumers will not face temporary but extreme prices for some products.

To show feasibility of the AgriTrade, we carry out a pilot use case, where a comparison is fulfilled between traditional farmer immediately selling their products and farmers storing and then selling their products based on the price forecast. To do so, we collected average tomato prices of the EU between 2004 and 2020 (Seyedmohammadi et al. 2018). We also derived the information of Antalya/Turkey (one of the biggest exporter of EU (The Ministry of Agriculture and Forestry of Turkey & TAGEM, 2018)) about tomato cultivation types, production pattern and gross production value (GPV) from (David-Benz et al. 2012; European Commission, 2020; Seyedmohammadi et al. 2018). In addition, we develop a Long Short Term Memory (LSTM)-based forecasting algorithm for AgriTrade. Finally, we calculate income of the farmers for two cases: 1) if they would store for one or two months and then sell their tomatoes according to the forecasted prices for the last five years, provided by the LSTM-based algorithm, or 2) if they would immediately sell their tomatoes. The results clearly denote that the farmers can increase their income around 9.1% and in total, Antalya farmers can earn around 2M euro additional money per year. This results shows that such an ICT-based system can help the farmers to rise their income, as well as moving towards more sustainable farming. The proposed system is a conceptual system, which needs furher investigation, reseach and implemtation to achieve more mature ICT-based agrifood system. However, this works presents a good starting point for the researchers to built such a system.

The remainder of the article is organized as follows: Section 2 discusses the related works. Subsequently, Section 3 introduces the concept and methodology of the proposed approach, called AgriTrade. Section 4 presents the evaluation of the proposed approach

2. Related Works

The proposed project spans on three distinct subjects in the study of the digital agriculture:

2.1. Market Information Systems (MIS)

Farmers contact with markets and each stages of the value chain via MIS. The market price, fluctuation over time, shows the whole demand for that product and value of current day. Without the MIS, farmers could not access these prices information, and thus relying on information obtained from local traders to identify when, whether, where, or for how much to offload their products (Deichmann et al. 2019). There are a number of empirical researches assessing the effect of market information on prices of farmers. The general results demonstrate that obtaining regular market information leads to around 15% higher prices in farm gates (Deichmann et al. 2019; Aker & Fafchamps, 2015; Fafchamps & Minten, 2012; David-Benz et al. 2012). Furthermore, the mobile apps used for MISs can benefits to the agricultural sector as follows a) accessing real-time agricultural product prices via mobile app enable farmers to sell their crops to higher prices. Also, obtaining accurate and online information about weather and diseases/pesticides provides better risk management. b) using the mobile app a farmer can obtain recommendations made by online system about farming practices, which causes higher crop yield in addition to higher quality crops (Trendov, et al. 2019). A practical use case for MIS: in Germany, some supply providers and farm services provides special solutions for individual farms and make recommendations to farmers to offer efficient, sustainable and economic ways for each farmer (Pesce et al. 2019; Giesler et al. 2020).

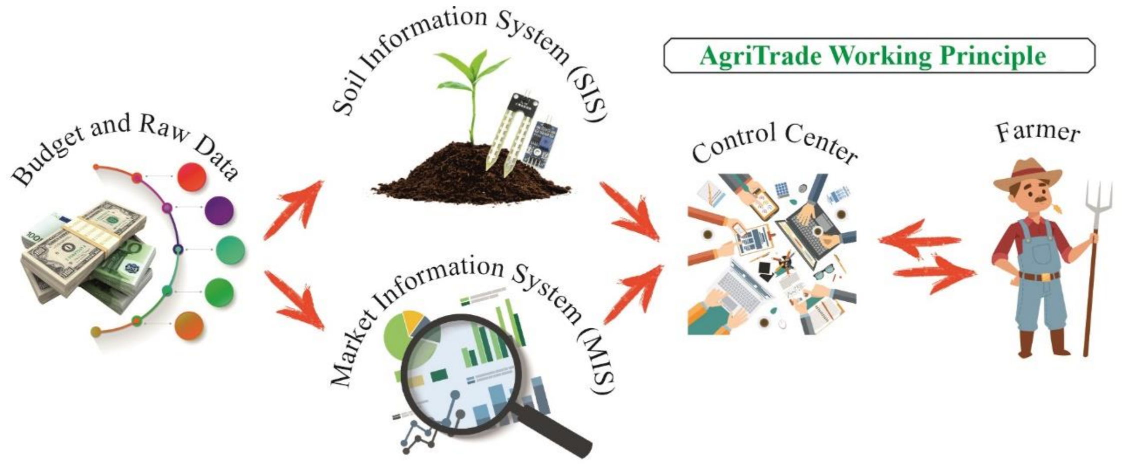

Figure 1: Conceptual Architectures of AgriTrade

2.2. Agricultural Decision Support Systems (ADSS)

The ADSS paves the way for selecting appropriate crops to be grown, pesticides, irrigation types by using the acquired field data (Antonopoulou eet al. 2010; Tayyebi et al. 2016; Bacco et al. 2019). Antonopoulou et al. (2010) proposes a Web-based ADSS, akin to AgriTrade. The app proposed by Antonopoulou et al. (2010) help to farmer to select appropriate crops for their farms for the cultivation period. SmartScape (Tayyebi et al. 2016) allows policymakers to assess the consequence of switching of agricultural products on diverse ecosystem services in agricultural regions by employing a ADSS and collected data. Foodlocker (Alawode et al. 2020), a Nigerian foodstuff and grocery aggregator, takes advantage of deep learning method for predicting demand for farm products and consumer goods. The API-AGRO provides a platform for sharing agricultural data for free obeying the ethical and legal rules in France. API-AGRO targets at cooperation of public and private actors, exploiting a technological platform, in order to introduce innovations for high-performance and sustainable agriculture (API-AGRO, 2019).

However, simply providing general agricultural information and software for individual tasks will not be useful for the agricultural sectors in the smart farming era, since farmers will require not only personalized per farm and farmer recommendations but also recommendations considering local and global markets, and ex-post prices. Moreover, collaboration of all smallholder farmers will require to perform a proper cultivation priority planning among the EU.

To fill this gap, in this paper, AgriTrade first makes personalized recommendations to farmers by exploiting the collected data across the whole agri-food chain. The most important contribution of our approach is to proportionally match the funding provided by EAFRD with the recommendations generated by AgriTrade in order to attract the farmers to the recommended cultivation plan. By doing so, AgriTrade will significantly contribute the alignment of supply and demand, sustainable farming and protection of climate, etc. in Europe.

3. Concept and Methodology

In this section, we will first introduce the main concept of our idea and then go into details about methodology of the proposed approach.

3.1. Concept

In this paper, we propose a holistic agricultural system, named AgriTrade, consisting of multiple agricultural policies and ICT-based methods. AgriTrade carries out a cultivation planning to regulate agricultural markets and international trade considering sustainability objectives. AgriTrade fulfills the cultivation planning, based on the data acquired from farms to markets across Europe. By doing so, AgriTrade plans to fix the imbalance between agricultural production and consumption inside Europe. Moreover, the export and import of agricultural products must be considered while embodying the cultivation planning. Therefore, the project considers the commodity exchange parameters in addition to the data of the agricultural markets in the cultivation planning.

On the other hand, in the cultivation planning, another crucial parameter is the field information including all geographical and soil information per field and farm. The proposed project builds a soil information system, which enables the AgriTrade to recommend right agricultural products to be planted for each farm across Europe in the cultivation planning.

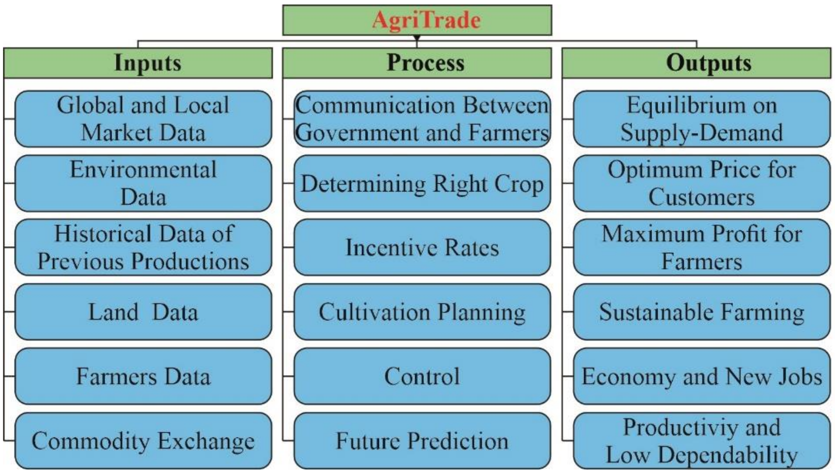

Figure 2: Overall Process of AgriTrade

The collection of various massive amounts of data for the cultivation planning necessities intelligent data management in addition to proper interpretation of the data. To do so, AgriTrade takes advantage of both cutting edge technologies such as machine learning and knowledge of experts in the finance and agriculture fields.

Assumptions

Implementation of AgriTrade, we have some assumptions as follows:

- All transactions of food supply chain between farms and markets are recorded and accessible in an online system e.g., when farming products are sold to any buyers.
- Land information, such as parcel and maps etc., can be obtained from an online system.
- Water information system for Europe (wise) can provide adequate information about irrigation water accessibility per fields.
- Uptodate wind, sunshine, precipitation, and humidity atlases can be derived from online systems.
- Soil analyses done by farmers (at least some of them) for each year is collected in Soil Information System (SIS).

Implementation of AgriTrade requires interdisciplinary collaboration among finance, agricultural, and ICT experts. Although agricultural production, marketing and digitization are the main works of finance, agricultural, and ICT experts respectively, they jointly work to implement AgriTrade. Fig. 1 depicts general working principle of AgriTrade.

AgriTrade will be validated using open data about agricultural markets and productions, which correspond to technology readiness level 4.

3.2. Methodology

The main idea of AgriTrade is to perform an interactive cultivation planning (between farmer and the control system), based on the collected data from agricultural markets, commodity exchange and land/soil information systems.

To do this, first, we propose an interactive incentive policy (IIP), which enables AgriTrade to direct farmers to grow appropriate agricultural products, as well as to let the administrators to know planted products before harvesting. This is carried out by developed the mobile app for farmers.

Furthermore, to offer correct incentives per farms, we propose a sustainable farmer-care agricultural production control policy, named SFAP. This policy enables AgriTrade to exploit the collected data from agricultural markets, commodity exchange and land/soil information systems in order to perform a proper cultivation planning. In addition, this policy takes into account sustainable farming and climate change mitigation while calculating the incentives.

To implement the proposed policies above, AgriTrade is equipped a digitalized system, which includes end users (farmers) and a control center. While the end user side enables farmers to cooperate in the cultivation planning via a simple interface app, the control center employs supervised machine learning technologies to provide continuous learning for the cultivation planning. In the following section, we introduce three main components of AgriTrade: Incentives, MIS, and SIS, followed by ICT-based main process. Fig. 2 shows inputs and outputs, as well as the processing steps of AgriTrade.

3.2.1. Incentives

The European Agricultural Fund for Rural Development (EAFRD) is the funding institution of the Common Agricultural Policy (CAP), supporting rural development strategies and projects. The budget amount of EAFRD (2014-20) is around 100 billion Euro. It is distributed according to six priorities: each of these priorities help the cross-cutting objectives: environment and climate change mitigation, adaptation, and innovation (cf. Pesce et al. 2019).

To achieve the above-mentioned priorities, IIP allows the system administrators to append multiple incentive parameters, affecting the AgriTrade's incentives calculation, such as:

- **P1 - Knowledge transfer & innovation:** Increasing incentive rate for farmers, investing for innovation and being open for cooperation and lifelong learning.
- **P2 – Competitiveness:** Increasing incentive rate for farmers, who have some regional disadvantages.
- **P3 – Food chain & risk management:** Increasing incentive rate for farmers, establishing/joining agricultural cooperatives for better marketing and quality, as well as for farmers insuring their farms and productions.

- **P4 – Ecosystems management:** Increasing incentive rate for farmers, following sustainable farming practices, such as preserving biodiversity, efficient water usage, preventing soil erosion, etc.
- **P5 - Resource efficiency & climate:** Increasing incentive rate for farmers, practicing organic farming to reduce ammonia emission and agri-environment-climate.
- **P6 - Social inclusion & local development:** The incentive policy of the AgriTrade helps farmers to grow products providing higher profits, thus supporting local development in rural areas.

3.2.2. Market Information System (MIS): Data acquiring, cleaning, preparation, analysis and exploration

AgriTrade is fed with multiple data sources in order to fulfill a proper cultivation plan according to SFAP policy. This data has to be gone through some stages such as cleaning, preparation, analysis and exploration.

Some of the data sources of the MIS of AgriTrade are listed as follows:

General Data:

- All transactions of agricultural productions (including past) obtained from each national Ministry of Finance in the EU.
- Import and export transactions of each agricultural product.
- Online commodity exchange data and wholesale prices of agricultural products

Data Per Farm(er):

- Land information.
- Historical data about agricultural productions per field.
- Historical data about consumption of agricultural productions.
- Information about disadvantaged areas
- Information about farmers that are open for innovative farming, cooperation, lifelong learning and agricultural insurance. This data can be obtained by local agricultural institutes, which follows farmers and enables cooperation between farmer and AgriTrade.
- Information about farmers that follow sustainable farming practices and are sensitive to climate change in the farming. This data can be obtained by corresponding institutes, i.e., local agricultural institutes.

The collected data has to be properly cleaned, prepared, explored and analysed before usage of the SFAP of AgriTrade for the cultivation planning. To do this, finance, agriculture and data experts work together. These experts seek patterns and correlations in the data considering the financial, agricultural and environmental issues behind the collected information. This collaboration creates a relational database, which allows the SFAP and IIP employed by AgriTrade to provide a proper cultivation planning and incentive rates, respectively. AgriTrade gives each farmer an identification (ID) and links the data with its respective farmer ID. By doing so, AgriTrade can personalize calculation offers and incentive rates per farmer and farm.

Moreover, these experts are responsible to prepare the training data sets, which are essential for the supervised ML algorithms of AgriTrade. The developed algorithms help SFAP to carry out optimum cultivation planning considering each farm's/farmer's individual characteristics and the local and global agricultural markets.

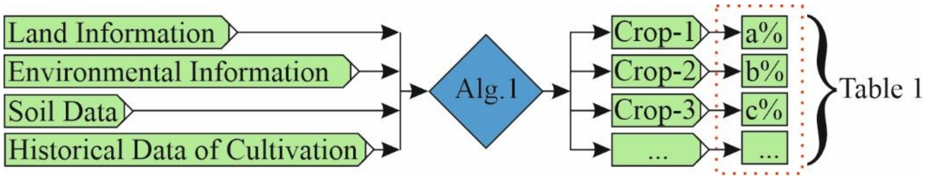

Figure 3: Finding appropriate crops for each farm considering SIS data (Step 1)

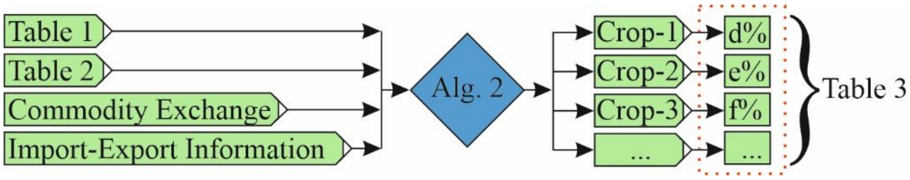

Figure 4: Selecting the "best" crops for each farm considering demand-supply and regional/global markets (Step 3)

3.2.3 Soil information system (SIS)

SFAP exploits following information while preparing planting offers per farm. SIS consists of the following datasets:

- Land information, including land record cadastre and associated attributes.
- Water, wind, sunshine, precipitation, and humidity atlases per farm/area
- A soil tests database. A soil test contains the analysises of soil samples from agrigultural fields to identify composition, nutrient content and other characteristics such as pH level or the acidity.

By using this information, it is able to offer suitable agricultural products, providing high profit and contributing sustainable farming. Furthermore, we consider that the soil database collects the soil test reports which are periodically performed by farmers in authorized laboratories. IIP also supports farmers who regularly carry out soil tests by giving higher incentive rate.

AgriTrade employs a supervised machine learning-based algorithm, which estimates each field's soil information (even no soil test for a field or not uptodate) by using existing soil test reports. Moreover, the supervised ML-based algorithm employed by AgriTrade uses the soil test reports, water, wind, sunshine, precipitation, and humidity information in order to find the suitable products to plant to each field.

3.2.4 ICT-based Main Process

AgriTrade fulfills the cultivation planning and calculates the incentive rates according to the IIP and SFAP policies, in 5 steps, which contain different algorithms.

STEP 1: Finding the right agricultural products per farm

In this step, AgriTrade exploits all information provided by SIS and historical information about agricultural production of MIS in order to find the right agricultural crops that give high yields.

The input data sets of Step 1 are as follows:

- Land information data set
- Data sets containing wind, water, sunshine, precipitation, and humidity atlases.
- Soil tests of fields
- Historical agricultural production data for each area
- The data sets comprising information about the effects of environmental factors, e.g., temperature, humidity and the acidity or pH level, on yield of each growing product (This data could be provided by Agricultural Experts for SIS).

Step 1 first uses a machine learning based method to estimate the soil information about the fields with no soil information. Then, Step. 1 finds optimal products for each field, considering the data derived from SIS, the data containing the environmental factors, and the historical agricultural production data for each area. The output data set is a database table (called Tab. 1) containing field ID and yields of each agricultural product, which shows which products are suitable to grow in which areas and farms. Overall progress of Step 1 is depicted in Fig. 3.

STEP 2: Prediction the coming year agricultural production consumption and price

In Step 2, AgriTrade employs a machine learning based estimation algorithms (see Section 4.2) to forecast the coming year consumption and price of each product.

The resulting data set of this step is saved in a database table (called Tab. 2) consisting of product ID and the consumption estimation.

STEP 3: Performing the basic cultivation planning and calculating incentive rates

The aim of Step 3 is to carry out the cultivation planning by using Tab. 1 (suitable products lists for each field), Tab. 2 (the next year consumption estimation), price forecasted prices, online information about commodity exchange, and wholesale prices. To attract farmers to grow the planned products in the cultivation planning, in this step, incentive rates are calculated for each farm.

Step 3 performs above-mentioned task according to policies defined by IIP and SFAP. Firstly, according to SFAP, for each product, Step 3 finds the "best" farms this product and then selects some of them providing, in total, the estimated consumption of the product. Then, it gives the highest incentive rate for this product in this fields, assuming the farmer will plant the offered product. In such a scenario, some farmers might not want to plant the offered product. Step 3 calculates second and third incentive rates for the other products (the incentive list can differ among farms based on Tab. 1). By doing so, in this step, the farmers are encouraged to realize the cultivation planning. According to the IIP, each farmer gets an amount of funding as incentive, which is based on the size of his field. Depending on the incentive rate calculated in Step 3, the amount of funding increases if the farmer grows the offered crop. The resulting data set is a database table (Tab. 3), containing farmer ID, field ID, incentive rates for each product. This process is illustrated in Fig. 4.

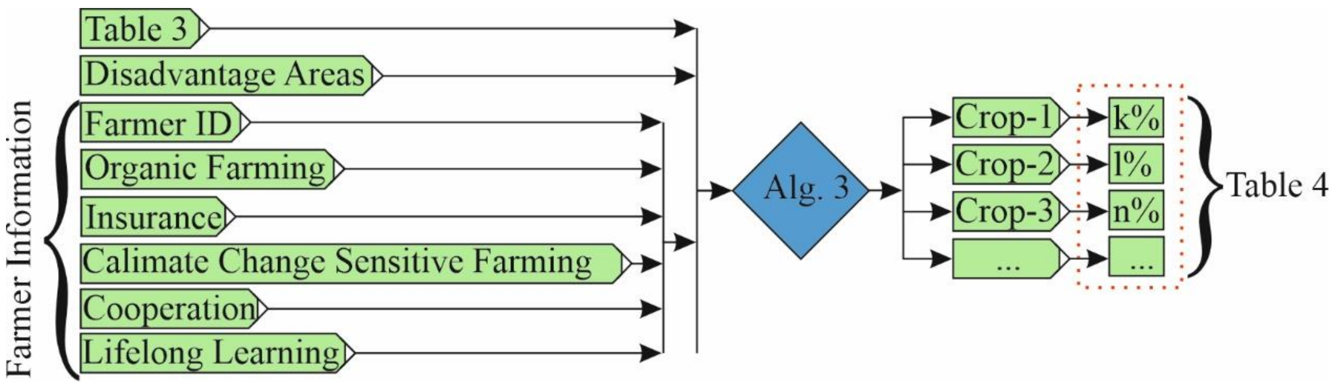

Figure 5: Adding incentives for the found crops each farm considering sustainability issues (Step 4)

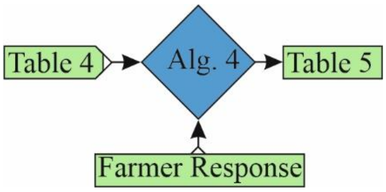

Figure 6: Re-planning depending on the farmers' feedback (Step 5)

STEP 4: Sustainable and Climate-change-aware farming

To encourage farmers for sustainable farming, in step 4, AgriTrade amends the incentive rates in the Tab. 3 according to the regional disadvantages and whether farmers are practicing the following criteria: Organic agriculture, Lifelong learning, Cooperation, Insurance, and Climate changing sensitive farming.

According to the IIP, the farmers performing the above-mentioned actions deserve higher incentive rates. By doing so, it is possible to reflect the impact of the internalisation of environmental costs on the competitiveness of agricultural production. The resultant data set is a database table (Tab. 4), the final version of Tab. 3, consisting of the incentive rate for each product of per field.

STEP 5: Interactive cultivation planning

The incentive rates in Tab. 4 will be introduced to farmers via a mobile app with a simple interface. If each farmer selects the product with the highest incentive rate, the cultivation plan would be properly performed. However, some farmers might select the other product with lower incentive rate. In this case, in Step 5, AgriTrade should recalculate the incentive rate and change the cultivation plan partially according to the farmers' preferences.

To show efficiency of the proposed policy, we will implement a small-scale pilot use case with real world data. The use case is as follows:

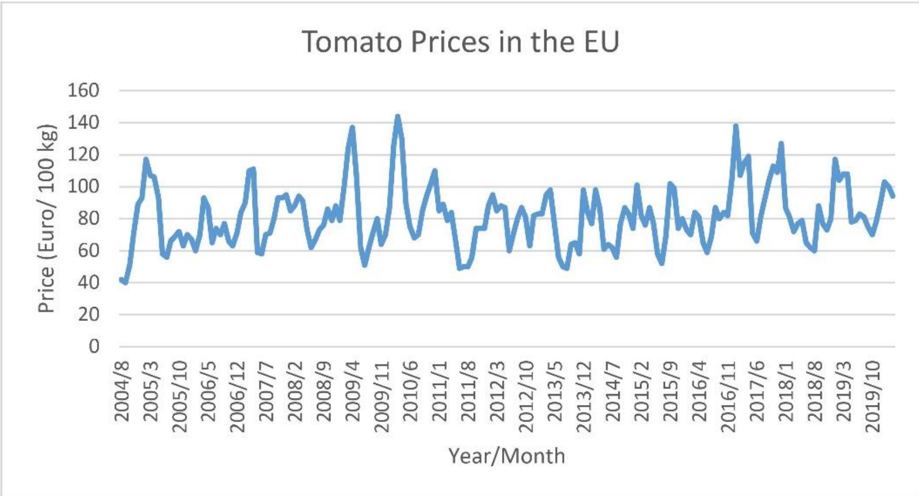

Figure 6: Original Average Tomato Prices for 100 kg (2004-2020) in the EU

4. Evaluation and Discussion

4.1 The Pilot Use Case

In Antalya/Turkey, most farmers planting tomato are not aware the fluctuation of tomato prices in the EU, which is one of the biggest importer of Antalya tomatoes (The Ministry of Agriculture and Forestry of Turkey, & TAGEM, 2018). When the farmers are informed by using AgriTrade, which analyzes the historical and real-time tomato prices and forecasts the future prices, they could store for one or two months or sell immediately their tomatoes. We will analyze the effect of the storage of tomatoes for one or two months on the income of the farmers.

Scenario: To show the feasibility of the idea, we acquired average tomato prices of the EU between 2004 and 2020 from dataset built by the EU (European Commission, 2020), which are depicted in Fig. 6. Moreover, we obtained the information about tomato cultivation types, gross production value (GPV) and production pattern of Antalya in Turkey (Çanakçı & Akıncı 2004; Özkan et al. 2001; The Ministry of Agriculture and Forestry of Turkey, & TAGEM, 2018). To forecast the coming year tomato prices, we develop a ML-based forecasting algorithm, using the historical tomato price data of the EU. Exploiting the historical EU tomato prices data, the developed algorithm forecasts the coming year tomato prices. A comparison between the traditional way marketing and the forecasting-based marketing in terms of their effect on the farmers' income is required to see our approach's efficiency. While the traditional way is to immediately sell the products when it is grown, the forecast-based marketing is to store the products until the time the product's price is higher according to the forecast (for tomato, storage time could be one or two months, but for other products this time could be longer).

In the next section, we will introduce the ML-based algorithm, which is developed to precisely forecast the coming year prices.

Table 2. Parameters of the developed LSTM mode

Layer (type)	Output Shape	Yield (Param #)
lstm (LSTM)	(None, 4)	96
dense (Dense)	(None, 1)	5
Total params: 101		
Trainable params:101		
Non-trainable params: 0		

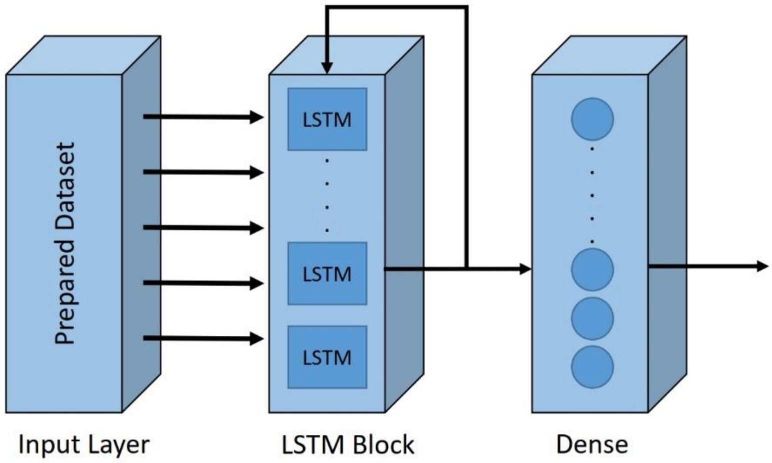

Figure 7: Presentation of the proposed model

4.2 The developed LSTM-based Forecasting Method

In this section, we will first introduce an overview of Long Short Term Memory, employed to developed the forecast algorithm, second, give details about the developed LSTM-model.

4.2.1 An Overview of Long Short Term Memory

Long Short Term Memory (LSTM) networks, are a specific version of recurrent neural networks (RNN), which are able to learn long-term dependencies and address the long-term dependency problem. LSTMs are capable of remembering information as a default for long periods of time (Hochreiter & Schmidhuber, 1997; Gers et al. 2002; Olah, 2020). While RNNs consist of a chain constructed with simple repeating modules of neural network, LSTMs' repeating modules includes four hidden layers with a special interaction between each other (Olah, 2020).

$$f(t) = \sigma\left(W_i.[h_{t-1} * X_t] + b_f\right)$$

In the first layer, LSTM uses a sigmoid layer to identifies which information to be dropped from the cell state, also called forget gate layer, considering prior output, h_{t-1} and input, x_t. The output f_t of the forget gate layer in equation above[2] is a number between 0 and 1, where 1 means that this should be totally saved and 0 means that this should be totally thrown away (Olah, 2020).

$$i_i = \sigma(W_i.[h_{t-1} * X_t] + b_i)$$

$$\mathsf{C}_t = tanh(W_c.[h_{t-1} * X_t] + b_c)$$

Now, it is time to identify which new information to be saved in the cell state. To do so, a sigmoid layer, named input gate layer (the second layer), identifies the values to be updated, which results in i_t. Also, a *tanh* layer (the third layer) builds a vector of the candidate values, $\mathbb{C}_t$. Equation above represents these operations (Olah, 2020).

$$C_t = f_t * C_{t-1} + i_t * \mathsf{C}_t$$

Now, we switch the old cell state, C_{t-1} with the new cell state C_t. The decision is done by previous steps, now it is time to apply it using equation above, which multiplies C_{t-1} (the old state) with f_t and then add $i_t * \mathbb{C}_t$ (new candidate values) (Gers et al. 2002).

Lastly, there is a need to identify what will be the output o_t that is found on the filtered cell state. This layer provides the output carrying out by employing equation below (Gers et al. 2002).

$$i_o = \sigma(W_o.[h_{t-1} * X_t] + b_o)$$

$$h_t = o_t\, tanh(C_t)$$

4.2.2 The developed LSTM-based Model

Since estimating tomato prices is a time series problem, where the order of the data is important, random data cannot be selected for the training of the model created. A normalization is applied to pull the data into the value ranges that the LSTM model will process. In this way, the data are converted into 0-1 intervals according to their values. The first part of the obtained data is employed for training the model, and the rest is used for validation and testing. It is aimed to train a single LSTM layer and test the model with these trained weights since the number of data is low and has a single feature. Since the LSTM model is a Recurrent Neural Network (RNN) model, it calculates the estimated value to be generated later in the calculation and recognition of the current value, keeping the error rate of the previous value in memory. The loss function values are created by calculating the values given to the input layer in the LSTM cell. These loss function values are thrown into the memory cell by comparing the

[2] W_i and b_f are the weight and bias

actual values. The value generated by the loss function is used to compute the weight and error value of each neuron in the network.

The parameters of the developed LSTM model are demonstrated in Table 1. Furthermore, the developed model is depicted as in Fig. 7. In our comprehensive tests shown below we will clearly see that the developed model provides an accurate forecast, particularly for price information.

4.2.3 Validation of the Use Case with the Scenario

Fig. 8 demonstrates the comparison the training and test results of the developed LSTM-based forecasting algorithm with the original tomato price data. We clearly see that despite the high fluctuation among months and also years, test results show that the proposed algorithm provides highly accurate results. Since the proposed method is validated with the test results, tomato prices of the coming year can be accurately forecasted. Fig. 9 denotes the forecast of the tomato price of the coming year, namely 2020/3-2021/3.

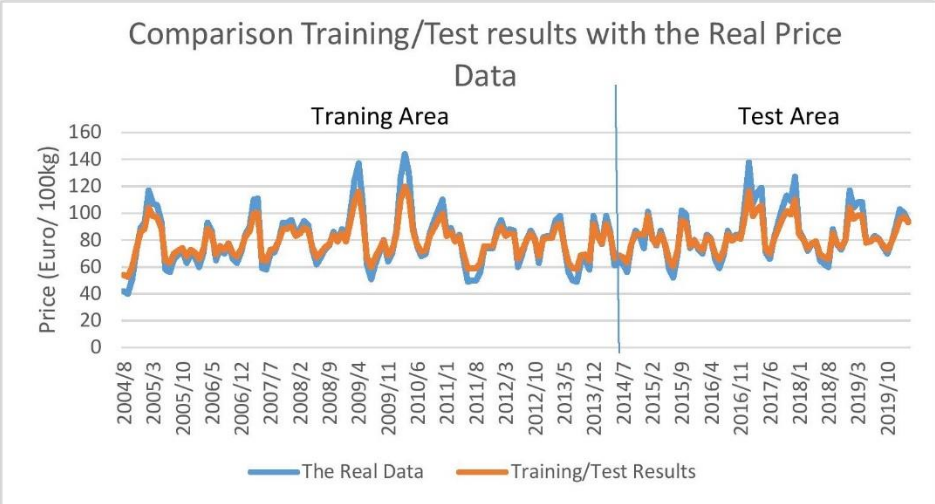

Figure 8: The comparison the original tomato prices with training and test price results

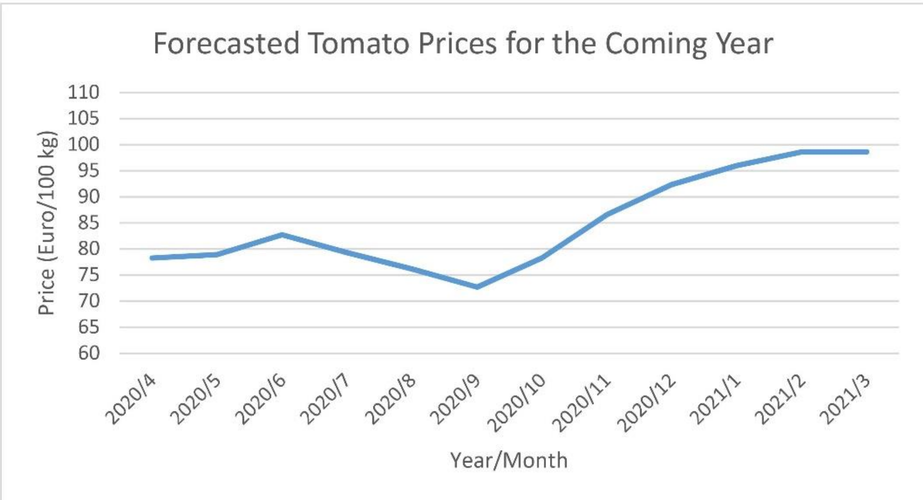

Figure 9: The forecasted tomato prices for the coming year, namely 2020/3-2021/3

Table 2. The tomato cultivation types, areas, yields of Antalya (Özkan et al. 2001).

Cultivation Types	Sown Area (ha)	Yield (kg/ha)
Single Winter Cultivation	109.5	13041
Spring Cultivation	68.6	10893
Fall Cultivation	70.1	8631
Open Field Cultivation (Summer)	33	3636

In Antalya, the farmers' cultivation types and yield of the farms are shown in Table 2 (Özkan et al. 2001). In this scenario, we simply consider that the farmers carrying out the respective cultivation type produce and sell their tomatoes in their respective season in a finely distributed manner. To illustrate this, farmers fulfilling the winter cultivation produce and equally sell their tomato in the winter months of a year, i.e., 12, 1, 2. In addition, we assume that the farmers have the ability to store their tomato for a few months. By using the forecasted tomato prices, they can save and then sell their product when the price is the highest according to the forecast. Based on this scenario, we calculated the total income if Antalya farmers would sell their tomatoes the last 5 years based on the forecast of the developed LSTM-based algorithm, or the "finely distributed manner". This calculation shows that if the farmer would sell their tomatoes according to the forecast versus the traditional way, they improved, in total, their income by average rate of 9.1 percentage a year (~2M Euro per year, based on the corresponding years tomato prices). Fig. 10 demonstrates the increase rates of the farmers' income for the last five years and the coming year if the farmers would sell their tomatoes according to the forecast. In Fig. 10, the doted straight line shows linear prediction line.

4.3 Discussion

This demonstration of the scenario clearly denotes that if the farmer can access the information about price forecasts of their crops, they could easily increase their income significantly. The accuracy of price forecast is of great importance for increase rate of the income of farmers. We clearly see that the LSTM-based forecast algorithm of AgriTrade developed in this work provides highly accurate results, which makes it feasible forecasting algorithm for forecast of prices of agricultural products in the future works.

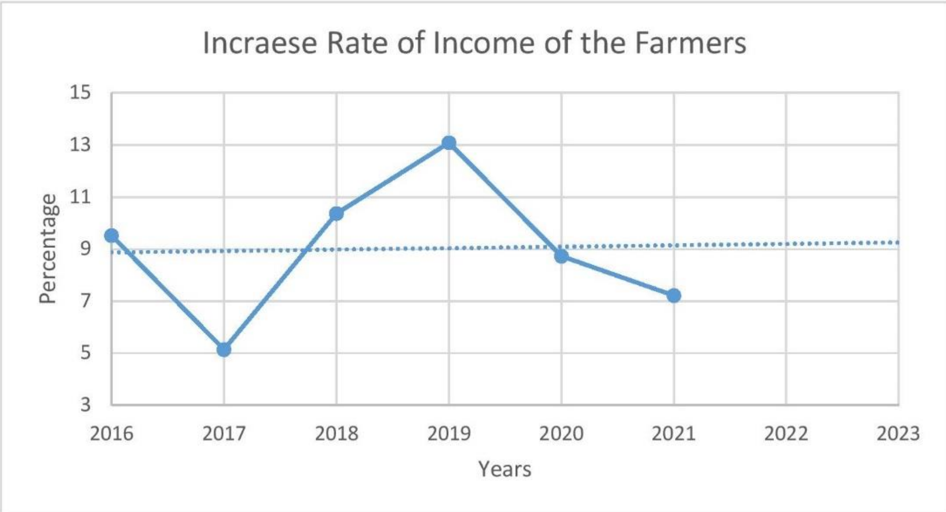

Figure 10: Increase rates of income of the farmers when they sell their tomatoes according to the forecast for the last five years and the coming year

5. Conclusion

In this work, we propose an ICT-based cultivation planning system, named AgriTrade, which offers to farmers the "best" agricultural products for their farms based on the price forecasting and soil analysis by employing the developed ML-based algorithms. Moreover, making use of the forecasted prices information, farmers can store their crops until the time the price is higher according to the predicted prices in order to sell their products at higher prices. AgriTrade introduces a holistic approach for the agrifood chain from farms to retailers, by collecting data from each participant of the chain to see big picture and by allowing interactive collaboration to control the system. Moreover, employing the developed LSTM-based algorithm, AgriTrade provides accurate price forecasting and soil analysis.

To demonstrate the feasibility of AgriTrade, we fulfilled a pilot use case, where we collected the last 15 years' tomato prices of the EU, as well as tomato cultivation types, sown areas, and yield information of Antalya, which is one of the biggest exporter of the EU. We compare the traditional way marketing and the forecast-based marketing. While in the traditional way, the farmers immediately sell their products after it is grown, in the forecast-based marketing, the farmers store their product for a few months and then sell it when the price is higher according to the prices forecasted by the developed LSTM-based algorithm. The results show that if the farmers sell their tomatoes based on the forecasted prices versus the traditional way, they would rise their income around 9.1% and in total, Antalya farmers can make 2M euro additional money, which shows the feasibility of the AgriTrade. Our future work will be to show the efficiency of our ML-based algorithms in prediction of soil analysis of a farm using other near farms' soil analysis data.

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