Crop yield prediction using satellite imagery data and deep learning

VARNIKA KAMRA, SJOERD KRUIK, BONO LARDINOIS, GIJS TIMMERIJ, and MAXIM VITALIS

Precision agriculture is a farming technique that uses technology to optimize crop yield and minimizes the wastage of resources, such as water for irrigation or pesticides for crops. This project is designed to serve this motive by generating crop yield predictions. Crop yield predictions can help farmers make data-driven decisions to use resources judiciously and modify farming styles to improve crop growth. To serve this motive, our stakeholder, AguroTech, targets using vegetation indices through satellite images and weather data. Remote sensing through satellite imagery data is an excellent source to fetch information about the vegetation indices, which include the Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and Soil Index. Instead of actual satellite images, satellite pixel data is fetched through the Sentinel API based on the spectrum band required for the last six years. With the collected and pre-processed remote sensing data, various models, including Prophet, Temporal Convolutional Network (TCN), and Long-Short Term Memory (LSTM) models, were tried on NDVI (historical), NDMI, and Soil Index data to predict NDVI for the next 14 days. However, The TCN model performed best for predicting NDVI with a Root mean squared error (RMSE) of 0.12. Lastly, this project incorporates textual advice to the farmers based on the predicted NDVI to optimize their yield and resources.

Additional Key Words and Phrases: Precision Agriculture, NDVI, TCN

1 INTRODUCTION

This project will examine new ways of getting more accurate predictions and giving better advice to farmers that make use of the services of Agurotech. Agurotech has made it its mission to make farming more sustainable by using less water to create a more efficient food-producing system. With an app, farmers get precise information about soil indices of their fields and get advice about what to do next. This close monitoring of the field trough the use of modern technology is called precision agriculture.

Precision agriculture is a farming management term that uses technology to optimize crop production and minimize waste. Crop yield prediction is one of the challenging problems in precision agriculture, and several models have been proposed so far in this domain. The major issues concerning crop yield predictions are taking into account various factors such as climate, rainfall, soil type, humidity, and nutrition [Xu et al. 2019] for its calculation. Every step in the crop cycle is equally important and plays a vital role in the actual production. An accurate crop yield prediction model can help farmers decide what to grow and when to grow.

Remote sensing, in particular, is a tool for precision agriculture, as it allows farmers to gather information about their fields from a distance. One critical parameter derived from remote sensing data are vegetation indexes, such as the Normalized Difference Vegetation Index (NDVI). The NDVI is a widely used indicator of vegetation health, as it provides a quantitative measure of the amount of green vegetation in an area.

The major challenge faced in remote sensing applications is the obstruction by clouds [Zhu et al. 2015], which will affect image composition and the calculation of vegetation indices like the NDVI [Huete et al. 2002]. Therefore, finding a way to collect data even when there are clouds is essential so that they will not interfere with crop monitoring.

Machine learning has become an increasingly popular tool for analyzing remote sensing data in precision agriculture in recent years. Machine learning algorithms can process large amounts of data and extract useful information that would be difficult or impossible to discern manually. Machine Learning models can determine patterns and correlations and discover knowledge from datasets[Van Klompenburg et al. 2020]. In particular, supervised learning algorithms can be trained to predict the NDVI from remote sensing data. These predictions can be used to identify areas of the field that need attention.

As described above, remote sensing and the NDVI are good tools for evaluating vegetation cover. Moreover, a good prediction of the NDVI can help monitor and manage farming crops. Hence why this study aims to explore the potential of satellite imagery for predicting NDVI and address two key questions: (1) How to collect (historical) data for NDVI prediction, and (2) what model performs best for NDVI prediction.

Satellite imagery provides a means of acquiring NDVI values from remote locations, enabling the generation of NDVI maps at high temporal and spatial resolutions. However, collecting reliable open-source historical data remains challenging. This study will address this challenge by investigating various methods for collecting historical NDVI data from satellite imagery.

After collecting reliable data, the choice of model for NDVI prediction is critical. Like mentioned before, various machine learning models have been applied for NDVI prediction, including Random Forest, Support Vector Regression, and Artificial Neural Networks. This study will implement and evaluate the performance of some of these models based on a literature review. Finally, an application will be built to guide farmers in making more data-driven decisions.

The findings of this study will provide valuable insights into the potential of satellite imagery for NDVI prediction and inform the development of more accurate and efficient methods for NDVI prediction. The results will be of interest to a wide range of stakeholders, including researchers, decision-makers, and practitioners in the fields of agriculture and environmental management. Moreover, this project specifically aims to extend the model Agurotech already has for predicting crop yield and giving better advice to the farmer.

Source code available at[1]

2 PROBLEM SPACE

The team of Agurotech is examining new ways to upgrade their systems to the next level. They want to do this by adding satellite imagery to their existing system and, with this, get more accurate crop yield predictions and give farmers better advice about what to

Authors' address: Varnika Kamra, varnika.kamra@student.uva.nl; Sjoerd Kruik, sjoerd.kruik@student.uva.nl; Bono Lardinois, bono.lardinois@student.uva.nl; Gijs Timmerij, gijs.timmerij@student.uva.nl; Maxim Vitalis, maxim.vitalis@student.uva.nl.

[1] https://github.com/TH3RMOMETER/Crop_yield_prediction

do next. This section describes the current system, the stakeholder's needs, and the end users' (farmers) needs.

The stakeholder (Agurotech) in this project seeks a way to get better predictions on a farmer's crop yield (the client), so they can be advised better on what to do next. Agurotech tries to push farming to the next level with smart applications for farmers. By monitoring what is happening in a farmer's field more precisely, there can be better and more efficient food production. The next promising trend in agriculture is precision farming. It is a way of more efficient food production and gives the farmers better possibilities in monitoring and advising what to do next. As of now, Agurotech is mainly working with sensors in the field that monitor soil conditions, push these statistics into their algorithm, and get results on crop yield. Next, they send the results via an app to the farmer so they can remotely monitor their crop growth. Moreover, Agurotech also advises on where on the field to take action. For example, some parts need to be watered, and others need pesticides. However, Agurotech was not the only stakeholder. We also needed to keep in mind the farmer. After meetings with agurotech, it became clear that farmers were looking for a simple-to-interpret interface that tells them what to do in certain situations.

To extend the application of Agurotech and make more accurate predictions on the crop yield, the team at Agurotech was looking to implement satellite images to predict variables like the NDVI (Normalized difference vegetation index). Next, add this to their existing model to make a more accurate prediction of the crop yield and what to do next for the farmers. To narrow this project's scope, our team decided to focus on the already-mentioned research questions. This meant we concentrated mainly on getting good-quality data through an open-source satellite to make it more cost-efficient for Agurotech. Moreover, we implemented models to predict the NDVI based on literature research. Finally, we build a user-friendly interface that predicts the NDVI for the coming 14 days and advises on what to do next. With these goals in mind, we started examining other existing solutions to this problem. These will be explained in the next section.

3 RELATED WORK

After identifying the requirements imposed by Agurotech for this project, the next step is to examine whether there are similar situations so valuable insights can be learned and applied to this project. This section describes some of the most noteworthy literature on combining vegetation indexes with weather, and models.

3.0.1 NDVI. Remote sensing has been used for many years to detect and predict vegetation indexes like NDVI and NDMI. This section will highlight some studies that used the NDVI and weather data. Moreover, this section will explain how the NDVI can be generated from remote sensing images.

The NDVI is a measure of the health of vegetation, as it is based on the amount of visible and near-infrared light that the vegetation reflects from the sun. NDVI is commonly used to monitor crop health and detect early signs of plant diseases. With remote sensing, it is possible to measure NDVI at the ground level, which can be used to compare and monitor crop growth over time. In addition, this method can also be used to measure the impact of environmental factors, such as weather, on crop health. To get data on the NDVI index, multiple satellite bands were combined. The different bands from a satellite all have a different electromagnetic spectrum range. This can be thought of as a color, but some bands will also have infrared bands which are not visible to the naked eye. The following formula can calculate the NDVI: NDVI = (NIR-Red) / (NIR+Red). In this formula, NIR means near-infrared light, and Red is the visible red light. [Avdan and Jovanovska 2016]

Recent studies have explored the use of remote sensing to predict NDVI in combination with weather data. For example, a study by [Gholamnia et al. 2019] combined satellite-derived NDVI data with precipitation data to predict the growth of wheat crops in the Fars Province of Iran. They found that using NDVI and precipitation data together was more accurate than using either dataset alone. Furthermore, another study by [Huang et al. 2019] used NDVI data in combination with temperature, humidity, and wind speed data to predict rice yield in China. They found that the combination of NDVI and weather data could predict rice yield accurately and that this was more accurate than using either dataset alone.

In addition to using NDVI and weather data to predict crop yield, this method can also be used to assess crop stress caused by environmental and management factors. For example, a study by [Peng et al. 2020] used NDVI and weather data to assess the effects of drought stress on corn crops in the United States. They found that a combination of NDVI and weather data could accurately predict the effects of drought on crop health. Furthermore, another study by [Huang et al. 2020] used NDVI and weather data to assess the effects of soil salinity on wheat crops in the Inner Mongolia Autonomous Region in China. They found that a combination of NDVI and weather data accurately predicted the effects of soil salinity on crop health.

Overall, remote sensing and weather data can be used together to predict NDVI accurately. This method can be used to provide valuable information on the health of crops and the impact of environmental factors on crop growth. Additionally, this method can improve crop management strategies, such as irrigation and fertilization, to optimize crop production. Moreover, this method can be used to assess the effects of environmental and management factors, such as drought and soil salinity, on crop health. As such, this method has the potential to provide valuable insights into the impact of climate change on crop production and can help to inform decisions regarding the use of resources, such as water and fertilizer, to optimize crop yield.

3.0.2 NDMI. Apart from vegetation variables, the information on soil moisture plays an essential role in the aspects of crop yield management and agricultural management practices.

As per [Karthikeyan et al. 2020], remote sensing can identify irrigated regions and the amount of water needed to fulfill the water shortage or the excess water content. A study conducted by [Letey 1985] explicitly determines the importance of moisture in the soil as a significant factor contributing to crop yield growth. Thus, the NDMI index is another crucial parameter for crop yield prediction due to the vitality of moisture in the crop cycle. NDMI detects moisture levels in vegetation using a combination of near-infrared (NIR) and short-wave infrared (SWIR) spectral bands. Using

NDMI to monitor irrigation, especially in areas where crops require more water than nature can supply, helps to improve crop growth significantly. The following formula can calculate the NDMI: NDMI = (NIR-SWIR) / (NIR+SWIR).

NDMI is a reliable indicator of crop water stress. It has been found that changes in environmental factors such as air temperature, air humidity, soil moisture, and wind speed are the parameters affecting NDMI. Deep learning approaches, i.e., a combination of rotation forests and decision trees, Neural Networks (NN), and Artificial Neural Networks (ANN), can successfully predict NDMI [Zhou et al. 2021]. A study [Watson-Hernández et al. 2022] successfully investigated the role of moisture indices and vegetation indices to predict the oil palm crop yield. Our model used the NDMI index and other parameters like historical NDVI data and Soil index to predict crop yield using the NDVI index.

3.1 Soil Index

Next, we concentrated our research on soil's physical properties and traits that influence crop yield. Soil properties are internal factors that can boost crop growth or diminish the expected yield [Letey 1985]. The farmers will likely have a low yield, even if water and pesticides are provided in an adequate amount.

The nutrients provided in the soil, the type of soil type, and pH value are general paradigms that affect the crop yield[Van Klompenburg et al. 2020].

Our findings are further strengthened by the study conducted by [Franz et al. 2020], which emphasizes the role of topography and soil condition in predicting crop yield. It also presents the importance of spatial and temporal scaling issues associated with field-based approaches. Due to the vitality of the soil and its properties in determining crop health and field state, we use Soil Index as an essential paradigm to predict the NDVI index.

3.2 Weather

Weather data, specifically precipitation and temperature data, can provide valuable information about the environment in which vegetation is growing. The use of weather data to predict NDVI values has been the subject of several studies in recent years.

A study conducted in China [Chuai et al. 2013] found that NDVI values were positively correlated with precipitation and temperature, with higher NDVI values observed in areas with higher precipitation and lower temperatures. The study also found that NDVI values were negatively correlated with evapotranspiration, which is the sum of evaporation and transpiration from vegetation. The study's authors suggested that vegetation growth is positively influenced by both precipitation and temperature but negatively influenced by high evapotranspiration rates.

Another study found that NDVI values were strongly positively correlated with precipitation and temperature. Here the NDVI was predicted for an area in Kansas. The study's authors suggested that NDVI can be used as an indicator of vegetation growth and productivity and that weather data like temperature and precipitation can be used to make NDVI predictions [Wang et al. 2003].

These studies demonstrate the potential for weather data to be used with NDVI data to make predictions about crop yields and vegetation health. By understanding the relationship between NDVI, precipitation, and temperature, researchers can make more accurate predictions about crop yields and vegetation health. This information can be used to optimize irrigation and fertilization practices, plan land use, and monitor for potential environmental hazards such as drought.

3.3 Models

This section will discuss models that have shown promising results in prediction time series data and in particular, time series data about the NDVI.

3.3.1 Deep learning. The widespread applications of neural networks and the recent advances in Computer vision and deep learning paved the way in various domains [LeCun et al. 2015], including remote sensing. Remote sensing is becoming increasingly important for crop yield prediction. The literature research is conducted to look for the existing models in this domain.

Due to the non-linear and complex features in the study, deep learning models can provide better insight by extracting features from layers. A model with Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) model [Sun et al. 2019] can fulfill our objective to study the fields (using satellite images) and the LSTM model to understand the field variations and changes over arbitrary time intervals. CNNs made it possible to investigate and study spatial features, and LSTM enhances the model by incorporating phenological characteristics. A CNN can learn the relevant features from the image, even the ones left unnoticed by human eyes. The use of LSTM can improve the efficiency of depicting temporal patterns at various frequencies, which is a desirable feature in the analysis of crop predictions as we need to have a good idea of the image over the period.

To extract the temporal dimension to get accurate models, the applications of Temporal Convolutional Networks (TCNs) [Wan et al. 2019] are considered next. TCN is a deep learning setup that considers the previous data and the current data to get accurate results. The evolution of the Temporal Convolutional Network (TCN) will benefit our interest in analyzing and using historical data for crop yield prediction with dilated convolutions.

TCNs outperformed canonical Recurrent Neural Networks (RNNs) for sequence modeling tasks and proved very effective in crop monitoring tasks. TCNs have added the computational advantage of processing convolutions in parallel instead of sequentially, as is the case in RNNs. TCN has shown promising results in time forecasting tasks and would be very beneficial for crop yield prediction. A deep learning-based TCN setup was done by [Gong et al. 2021] to predict the crop yield based on the historical data. A sliding window is used to get the input sequence, so the window length is specified according to the need. The results of the previous sliding windows are also considered while calculating the future predictions to capture all the irregularities and dependencies in the data and provide better results.

3.3.2 Prophet. Finally, the Prophet forecasting algorithm showed promising results in terms of predicting vegetation indexes if they have a strong seasonality. The Prophet forecasting algorithm is developed by Facebook and is a Bayesian time series forecasting algorithm. The algorithm combines trend analysis and seasonality analysis and has a built "holiday effect". Because Vegetation often shows a strong seasonality and has a clear trend, this could make a well-suited NDVI predictor algorithm. Moreover, the holiday component of the algorithm allows it to handle unknown events or outliers that could have a significant effect when doing trend analysis. Finally, the prophet algorithm is an easy-to-use algorithm that does not take much time to set up. [Taylor and Letham 2018]

Although articles on using Prophet to predict NDVI or other vegetation indexes are limited, there are studies that show promising results in predicting temperature and land change analysis. For example, a study by [Asha et al. 2020] showed that the Prophet algorithm for forecasting temperature was nearly as good as the Random forest model. But the Propet algorithm was easier to set up, which was a significant advantage.

Another study by [Yan et al. 2019] used to Prophet algorithm to forecast land change using remote sensing. Their results were promising as they achieved a 90% accuracy with the use of the Prophet. They conclude that using Prophet helped them predict the change in land coverage.

The mentioned studies show that the Prophet algorithm can predict the NDVI. The algorithm can model trends, seasonality, and holiday effects for time series data. It could be useful for NDVI prediction, especially in environmental monitoring.

4 METHODS

In this section, the methods used for this study will be discussed. First, the data collection will be discussed. Next, the models used will be discussed.

4.1 Data collection

In this section, the data gathering will be described for this project. We will start by explaining the data gathered via the sentinel API; next, we will explain how the weather data was gathered.

4.1.1 Sentinel API. To gather data for this research project, we aimed to collect historical data on NDVI, NDMI, and soil index for specific areas in the Netherlands. We chose to use the Sentinel API[2] as it provides open access to loads of satellite data from Sentinel-1, Sentinel-2, Sentinel-3, and Sentinel-5P. The Sentinel API is controlled by the European Space Agency (ESA). The data provided by the API includes imagery, products, and services related to land, ocean, and atmosphere monitoring.

To pull data from the sentinel API, a GEOJSON file that described the polygons of the areas of interest was created. The GEOJSON file format is a widely adopted standard for encoding geographic data and was utilized to specify these polygons.

Then, queries were created for every polygon and added to a list. Such a query consists of a time period for which we want to pull the data, aggregation level, resolution and a JavaScript file which tells the API which bands to pull and which calculations to perform. The list with all the individual requests is then send to the client, the client is then able to aggregate the list into a single query. This aggregation of queries enables the API to retrieve them in parallel, greatly increasing the speed of the request. The geographical and temporal resolution of the data, such as 10m or 20m resolution, is referred to as the aggregate level. The pixel size of the data is referred to as the resolution.

The data returned from the API was then converted into a Pandas data frame, a Python library for data analysis. This allowed us to easily manipulate, clean, and analyze the data. [McKinney 2010]

This strategy did have a drawback, though, in that cloud coverage prevented us from collecting enough data for some areas and time periods. To overcome this problem, we increased the amount of data points using an interpolation technique called Akima from the Scipy library to get around this restriction. Scipy is another python library and the Akima interpolation is a technique for interpolating data that combines spline methods. It is appropriate for data with significant gaps or erratic time intervals, as is the case with satellite data. [Virtanen et al. 2020]

Finally, to improve the computational efficiency of the data, we solely used the statistics from the Sentinel hub and avoided using any satellite image data. By employing statistics instead of image files, we were able to train the final models much more quicker by avoiding the need for a lot of memory and processing resources. The use of the Sentinel API pipeline was done for 46 different polygons trough out the Netherlands. This was our initial data collection for the NDVI and other soil indices.

4.1.2 Weather API. In addition to the satellite data we collected via the Sentinel API, we also gathered weather data for each polygon and timestamp using the Meteostat API. The Meteostat API[3] is a service that provides access to historical weather data from various weather stations around the world. It allows users to request specific weather data, such as temperature, precipitation, wind speed, etc., for a given location and period.

We used the Meteostat API to retrieve weather data for each polygon and timestamp we collected from the Sentinel API. This allowed us to combine satellite data with weather data to completely understand each area's environment. The weather data we collected from the Meteostat API was also put into the Pandas data frame along with the satellite data, allowing for easy manipulation, cleaning, and analysis of both datasets.

By gathering data via both the Sentinel API and Meteostat API, we combined satellite data with weather data to better understand each area's environment. The data obtained from the Sentinel API and Meteostat API were put into the same pandas data frame.

4.2 EDA and Data Cleaning

The next major step for this project is to investigate the correct data that can be fed to the data. The first step in this regard is to filter bad-quality data. Temperature and precipitation are the primary factors influencing crop yield, so good data is necessary. We plot the graphs for temperature and precipitation for the last six years and explored the variation and availability of data for these points in the parts of the Netherlands. The polygons with incomplete data are left out. In the figures below, an example of a complete good-quality

[2]https://sentinelsat.readthedocs.io/en/latest/api_overview.html

[3]https://dev.meteostat.net/api/

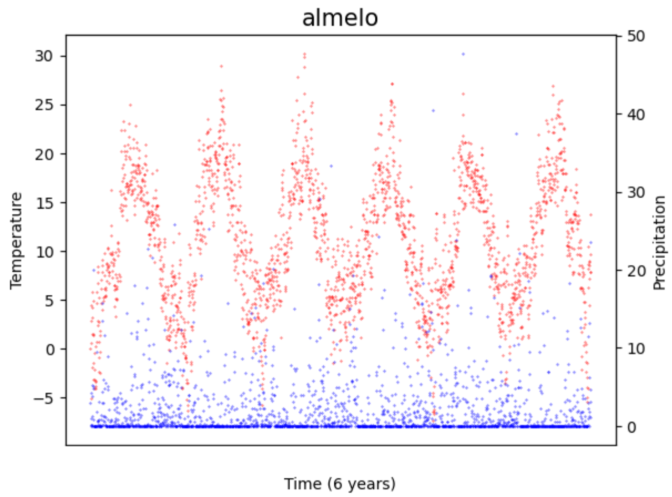

Fig. 1. Six years of weather data for a polygon near Almelo. In the blue precipitation and in the red temperature. This is an example of good data, as a strong seasonality can be seen with six temperature peaks.

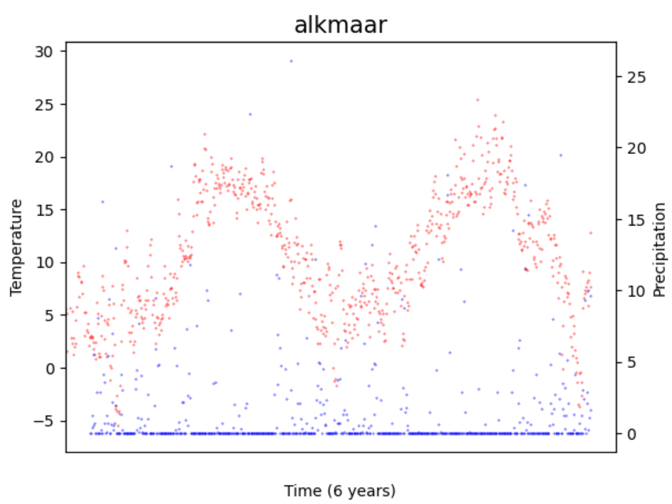

Fig. 2. Six years of weather data for a polygon near Alkmaar. In the blue precipitation and in the red temperature. This is an example of bad data, as the data is sparse and the seasonality is not yearly.

dataset (figure 1) and incomplete bad-quality dataset (figure 2) data can be found.

After analyzing the weather data for every polygon, 23 of the 46 polygons were kept, which resulted in ~ 50.000 individual data points, with one data point representing one day in one polygon.

Next, statistical analysis is done to find the relevant bands of the data. For this, we looked for the indices helpful in predicting crop yield, viz., NDVI, NDVI RE1, NDMI, NBSI, and CLP. To calculate these indices, we looked for the spectrum bands to get the correct data.

Another pre-processing step that was taken was to apply a sliding window to the time-series data. A representation of what a sliding window does can be seen in figure 3. For this project, a sliding window length of 14 was taken such that the model predicts the next two weeks based on the input of the last two weeks. So every data point consists of 14 time-series points, and for the following data point, the window slides one over. In figure 3, the window length is eight, and the stride (how much it slides over) is one. This technique is applied to every individual polygon.

Fig. 3. Simple representation of the sliding window technique

4.3 Models

In this section, a description follows of how to models were implemented and set up. We will start with the most simple model and progress to more complex models.

4.3.1 Prophet. After the data cleaning, the Prophet model was built with the use of the Prophet library.

Next, a model was built for each polygon, and a prediction was made for the coming 14 days after the last timestamp of that polygon. After this, each model was evaluated with the mean squared error (MSE), and the root mean squared error (RMSE). The statistics on these evaluation metrics were then saved in a pandas data frame. Finally, an average RMSE was calculated to compare the prophet algorithm to the other algorithms.

4.3.2 TCN. Before model building, the sliding window technique is used as a pre-processing step to deal with large and complex data, wherein smaller and overlapping windows of size 14 are created. This can learn about the local dependencies within each window. Sliding window panel is formed by considering NDVI mean (vegetation index), NDMI mean (moisture index), NBSI mean (soil index), tavg shift (temperature) and prcp shift (precipitation) as the x-values and NDVI mean 14 days in the future as the y-value (output).

These input sequences are then fed to the TCN model, which is a combination of residual blocks. These residual blocks are, in turn, a sequence of dilated convolution layer, batch normalization layer, and ReLU layer, whose primary goal is to make model memory efficient. This model can safely predict NDVI for the coming 14 time stamps (days) from the current day and subsequently for the next 14 days when the current day shifts. Thus, the future NDVI is predicted with the historical NDVI data, NDMI, Soil index, temperature and precipitation.

To investigate the best hyperparameters for the model, hyperparameter optimization was done using the Weights and Biases platform [4]. Drop-out rate, kernel size, learning rate, and the number of filters are the major parameters that affect the model. So, the validation loss was calculated by varying these parameters using a bayesian hyperparameter search algorithm to get the most optimal model. Interestingly, a set of varying these hyperparameters eventually led to roughly the same validation loss. After this, the TCN model was evaluated based on the mean squared error (MSE) and the root mean squared error (RMSE) to compare to the other models. Below in figure 4, a visual representation of the different hyperparameters tuned can be found.

4.3.3 LSTM. Lastly, Long Short Term Memory (LSTM) model was built to capture the historical data. A similar sliding window as TCN is generated with the same size as 14 and the same window panel. The model was eventually trained with three LSTM layers with a 10% drop-out rate in a sequential manner, followed by the final Dense layer with Softmax activation. Similar evaluation metrics, mean squared error (MSE), and the root mean squared error (RMSE) were used to compare this model with the other models.

4.4 Interface

This section will explain how the user interface was built and how it has been tested to improve its usability based on user feedback.

4.4.1 Building the Interface. For building the interface, the CustomTKinter[5] package for Python was used. This package allowed the user to integrate the interface with the model and data in a Pythonic fashion. The goal of the interface is to have a clear and uncluttered design with an obvious intention for all visual parts. To this end, the interface was divided into multiple vertical sections. The first section has buttons and input blocks that the user interacts with. Here, the user has access to all functionality and can select the plots as well as the data for which a prediction is needed.

Furthermore, buttons to change between different map views and the option to add markers to the map, were added to this section of the interface. Next to this section, a map overview of the selected plot is presented. This is to show the exact shape of the agricultural polygon and give context by showing a wider area. The final section of the interface shows the output of the model in terms of the predicted NDVI value for the coming 14 days. The output is presented as a graph with the labeled axis.

4.4.2 User Validation. The initial interface was shown during a meeting with the Agurotech team, and feedback was incorporated into the next version. With the second version, we performed user validation, asking the participants to perform several tasks and collecting feedback from this.

User validation tests if an interface is easy to use and tests if the outcomes are understandable. For this study, a group of people was asked to perform several tasks and report this in a form. The form consisted of three tasks that the user had to perform, but the person also had to rate the task from one to five on the ease of use (1 being the worst and five being the easiest to use). Moreover, the test subject would also have to give some short comments on how easy or hard it was to perform the given task. Finally, some additional comments were asked if there were any. The form was the same in all test cases and can be found in the appendix.

4.5 Team management

At the beginning of this research, the problem statement, the objective, and the desired solution were unclear to the team. The team immediately scheduled a meeting every Thursday. Additionally to the meetings, a schedule was created to document the focus on each phase and the purpose of each meeting. During the ideation phase, the team mainly conducted literature research and finding good-quality open-source data relevant to this research. Next, the team started the implementation/evaluation phase later than scheduled. This was compensated for by finalizing this phase during the last week of December and the first week of January. From the second week of January, the team scheduled meetings twice a day on each day of the week. The team believed that task dividing, alignment, and discussing progress on short notice was vital to completing this research successfully.

5 RESULTS

In this section, the results of this study will be discussed. Starting with the results of the good-quality data collection, next, the performance of each model will be discussed.

5.1 Model Results

This study evaluated three models: the Prophet model, Temporal Convolutional Network (TCN), and Long Short-Term Memory (LSTM). The evaluation metric used to measure the performance of each model is the RMSE. The results of this evaluation were as follows: the lowest RMSE was achieved by fine-tuning the TCN model (RMSE: 0.12), followed by the Prophet model (average RMSE: 0.14), and lastly, the LSTM (RMSE: 0.72).

The TCN model achieved the best accuracy in predicting the NDVI from historical data. Although the TCN model has slightly better accuracy than the Prophet model, it is more valuable because it encaptures the data from all polygons used. However, the Prophet model had to be trained for each polygon individually. Finally, the LSTM model had the lowest accuracy, with an RMSE of 0.72. This is primarily due to its difficulty in capturing long-term dependencies. The results show that the TCN model performed the best, so we continued with this model for our final application.

Model	RMSE
LSTM	0.72
Prophet	0.14
TCN	0.12

5.2 Interface

After showing our first version to the team of Agurotech, we got feedback on improving our interface. Taking into account this feedback from stakeholders, a weather prediction panel and textual feedback for the farmer have been added to increase overall user-friendliness. This has enabled a more comprehensive and accurate forecasting approach and provides a more reliable and efficient way

[4] https://wandb.ai/site
[5] https://github.com/TomSchimansky/CustomTkinter

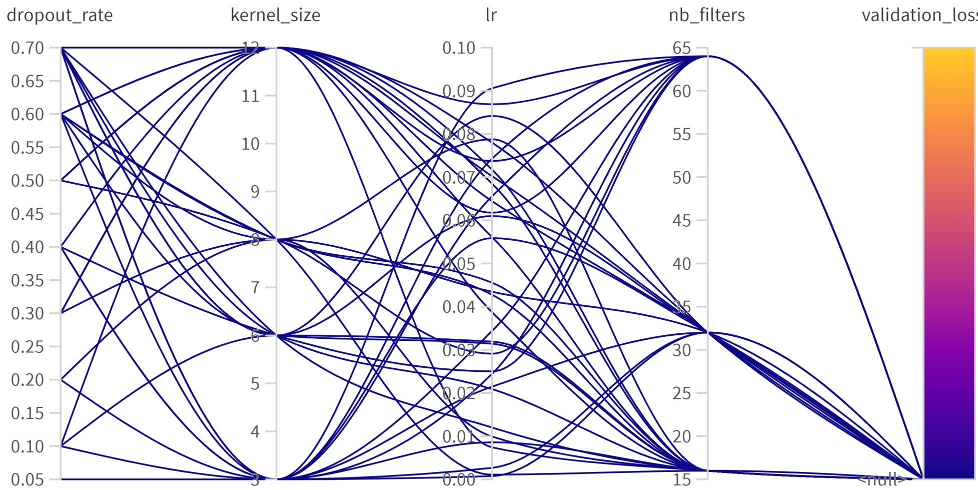

Fig. 4. A visualization of a Weights and Biases sweep showing all different configurations of hyperparameters tried, with every line depicting a configuration that was run and tested.

for farmers to stay informed about the conditions of their land. This addition allows anyone to make sense of the data and also understand how the weather predictions influence the NDVI results. This makes the results of the model more explainable and also more actionable.

The tests conducted on this second version mainly got excellent user feedback, as seen in the appendix. Test subjects often said it was easy and straightforward to put in data and that the results were also easily interpretable. From the comments, we also felt that the textual representation of what to next was an excellent addition to the application and made it more interpretable for all users.

6 DISCUSSION

With this project, Agurotech seeks enhancements to their product in order to get better predictions on the crop yield of the farmer, preferably by adding satellite imagery. With the results of this research, we believe that the developed prediction model is an additional value to the existing prediction model of Agurotech since satellite imagery and weather data is combined and included. The solution provides actionable feedback, whether to irrigate the soil or not, for the farmer based on the data and the developed model. What the solution does not provide is an accurate prediction about the crop yield. However, the provided solution intends to optimize the crop yield with its prediction model and actionable feedback.

One of the limitations of this project included finding relevant datasets for historical data from satellites with high resolution and high frequency. After an extensive search, we found that access to frequent high-resolution satellite data was limited and costly.

To circumvent this limitation, we explored alternative methods to access satellite data. These included researching public and open-access databases that provide high-resolution satellite imagery and using various software tools to integrate the data with the weather data. Additionally, the team sought out potential sources of free satellite data. Ultimately, we found an appropriate source of free satellite data, allowing us to continue their research without the additional financial burden. Although this data that was free to use was good, it can constantly be improved. Paid satellite data services offer, for example, better frequency and higher image resolution, which makes it useable for even more precise predictions.

Another improvement that can be made is regarding the testing of the application. Testing the application with the end-users—namely the farmers—is paramount for the project's success. However, this was not feasible due to the lack of communication links and time constraints. Their feedback is invaluable and will provide a better understanding of the application's suitability and performance. Testing the application with the farmers would enable the project team to understand if it meets the farmers' needs and expectations and if it produces the desired outcomes. Moreover, the farmers' suggestions and observations could be considered for further refinements and improvements. This farmer testing could enhance the scope of development for the project and should be experimented with in follow-up research.

A key strength of this research is the technical feasibility of implementing a TCN model into the current predictive model for NDVI values of Agurotech. Using statistics instead of images is computationally efficient and enables the study to generate models that can be compared in a limited amount of time. Moreover, the advantages of using a TCN model to predict NDVI values for Agurotech are multi-fold.

Firstly, the model created can capture the complex spatial and temporal correlation between crop fields and environmental conditions.

Secondly, the model can capture the dynamic nature of NDVI values over time and identifies how crop parameters such as soil moisture, temperature, and nutrient content affect NDVI values.

Finally, tracking the temporal changes in NDVI values can help farmers identify potential issues with their crop fields before they become a major problem. By implementing this model into the current predictive model, Agurotech can ensure that its customers are provided with accurate and up-to-date information regarding the health of their crops.

7 CONCLUSION

This study aimed to demonstrate the potential of open-source data from satellites for obtaining high-quality data and developing an accurate prediction model for NDVI (Normalized Difference Vegetation Index) through satellite imagery to help Agurotech improve their model and give better advice to farmers on what to do next. The study tested three models but eventually used a TCN model to predict NDVI and demonstrated its efficacy through the results obtained. The proof of concept developed in this study represents a significant contribution to the existing models used by Agurotech and highlights the potential of utilizing TCN for NDVI prediction.

The interface was designed with the farmer as the user in mind and was further developed with the feedback from the team of Agurotech and tests conducted on users. The approach, with several feedback moments, allowed us to create a user-friendly and practical interface for its intended audience. With the current model, Agurotech can provide farmers with more precise and accurate advice on maximizing yield potential.

Returning to the research questions, it can safely be stated that this study has answered them. (1) How to collect (historical) data for NDVI prediction was answered using the sentinel-hub API and weather data from meteostat. Moreover, the data used from the sentinel-hub were only statistics to make it computationally more efficient. We also used an interpolation technique to circumvent the clouds on certain days, which provided us with a usable data-set.

(2) On the question of what model performs best for NDVI prediction. We tried several models based on a literature study, and it can be concluded from the models tested that the TCN model performs best at predicting the NDVI with the specified predictors.

In terms of future work, further research could be conducted to improve the model's accuracy by using other open-source data portals or using some of the paid options to get better resolution and a better frequency of data. Moreover, combining several sources could also be fruitful in collecting data. The higher resolution means that instead of predicting the NDVI for an entire plot, predictions can be made for regions in the plot. This will give the farmer higher quality information about the plot of land and can make decisions on which part to irrigate/fertilize and how much.

Furthermore, additional features could be integrated into the interface to give farmers more detailed insights into their crops. Additionally, other predictive models could be explored to further improve the accuracy of NDVI prediction, or new predictors could be tested in the model to predict the NDVI.

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A APPENDIX

A.1 User Testing

"Hello, we are testing a new application that predicts NDVI (Normalized Difference Vegetation Index) from data and advises farmers about what action to take next to get a better crop yield. This test aims to see if the application is easy to use and if you understand the output. (Rate 1 - 5)

Task 1: Inputting Data. We would like you to input a date and select a plot of land and see how the application handles the data. Please tell us what you think of the process of inputting data.

Task 2: Reading the output. Please give us feedback on what you see and whether it's clear what the output is. What do you think when seeing the results?

Task 3: What to do. After interpreting the results, is it clear to you what to do next for the data that you've put in?

Thank you for taking the time to participate in this test. Your feedback is very valuable to us. Please let us know if you have any additional thoughts or comments about the application."

respondent 1: Task 1: Inputting Data.

(1) Rating: 4/5 : The process of inputting data was relatively straightforward and user-friendly. I had no issues finding the date and selecting a plot of land.

Task 2: Reading the Output.

(1) Rating: 4/5 : Feedback: The output was clear and easy to understand. The results were visually presented in a way that made it simple to interpret what the data was showing. I felt confident in my interpretation of the results.

Task 3 interpretation of the output:

(1) Rating: 4/5
(2) Feedback: Feedback: Based on the output, it was clear to me what actions I could take next to improve crop yield. The application provided practical advice that I could use to make informed decisions about crops.

Additional Thoughts/Comments:

Overall, I found the application to be very helpful and easy to use. The user interface was well-designed, and I had no trouble navigating the different features. I think this application has great potential for helping farmers improve their crop yields and I look forward to seeing how it develops in the future.

Respondent 2

Task 1: Inputting Data.

Rating: 5/5 Feedback: Inputting the data was a breeze. The interface was intuitive and made it very easy to select the date and plot of land.

Task 2: Reading the Output.

Rating: 3/5 Feedback: The output was partially clear, but I found it difficult to interpret some of the results. The visual representations of the data could be improved to make them easier to understand.

Task 3: interpretation of the output.

Rating: 3/5 Feedback: It was somewhat unclear what actions to take based on the output. I had trouble determining what the results were telling me and what I should do next to improve crop yield.

Additional Thoughts/Comments: This application has a lot of potential, but it needs some work. The user interface could be improved, and the output could be made clearer and easier to understand. With some refinement, I think this application could be very helpful to farmers.

respondent 3: Task 1: Inputting Data.

(1) Rating: 5/5 : The process was fairly straightforward and the information was easy to enter.

Task 2: Reading the Output.

(1) Rating: 4/5 : Feedback: The results were clear and easy to understand. It was easy to interpret the output and see the predictions for the NDVI value.

Task 3 interpretation of the output:

(1) Rating: 3/5 : Feedback: It was generally clear what to do next in order to optimize the crop yield, but I would have liked more detailed advice about how to take action.

respondent 4: Task 1: Inputting Data.

(1) Rating: 4/5 : The process of inputting data was quite straightforward and intuitive. I found the dropdown menus and the date selection process to be very user-friendly and easy to understand.

Task 2: Reading the Output.

(1) Rating: 4/5
(2) Feedback: The findings were presented in a manner that was simple to comprehend, and I was able to get an understanding of the significance of the NDVI values.

Task 3 interpretation of the output:

(1) Rating: 3/5 : Feedback: The application needs to make it easier to interpret the output. Perhaps by providing more detailed explanations or providing visual aids to help explain the output. The application should also offer more guidance on what action to take next, based on the data that has been input into the application.