Climate Services for Organic Fruit Production in Valencia Region: Early frost forecasting

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Abstract

The increased occurrence of extreme weather events due to climate change has heightened the need to develop support decision systems that can help farmers to mitigate losses in agriculture. Environmental hazards, such as frost have a relevant economy impact on crops since they may cause several damages and injuries in sensitive crops and therefore lead to production losses. Probability of frost occurrences are heavily influenced by local climate conditions. In addition, the extent of damage due to frost also depends on the phenology stages of the crops present at the area of interest. Hence, an early frost warning system at local scale have the potential to minimize damage to the crops as one can deploy protection mechanisms. In this article, we present models for an early forecasting (24 hours and 48 hours) of frost occurrences using stacked machine learning models. We trained the machine-learning models with hourly historical data from local weather station. The trained model is validated within the timeframe when the crops (organic fruits) are most susceptible to frost for the area of study. We also show the applicability of the model by extrapolating it to a new region. This development is carried out within the framework of H2020 CYBELE project.

1 Introduction

The increased occurrence of extreme weather events due to climate change has heightened the need to develop support decision systems that can help farmers to mitigate losses in agriculture. Environmental hazards, such as frost, have a relevant economy impact on crops since they may cause several damages and injuries in sensitive crops and, therefore, production losses. Frost is a serious problem for horticultural / fruit-trees production both early and late in the season since water within the plants and/or fruits may freeze during a frost event. The climate condition influence the occurrence probability of this kind of event, together with other issues such as vegetation presence, topography and soil type with relevance at local scale. Passive and active protection methods for frost exist in the market with their different characteristics, effects and costs. Based on the previous affirmation, early warning systems at local scale with a suitable spatial resolution on frost occurrence and their associated risks are relevant for agriculture. A Frost forecast system might help farmers to reduce any possible injuries to their crops since protection methods can be used. In Valencia region the compensations due to extreme weather events amounted to 9 million euros in 2020 and the previsions to 2021 would amount to 4.61 million euros according to the last Agroseguro report [1].

This paper covers forecasting of frost occurrences using machine learning techniques based on historical data. The Area of Interest (AoI) consists of two different agrarian lands located in Carlet and Belgida municipalities into the Valencia Region. Due to the agricultural practices in the AoIs, farmers usually need 24 to 48 hours to prepare for frost protection. As a result, this paper focuses on 24 hour and 48 hour forecasting of frost event. Frost forecasting is a challenging problem due to inherent chaotic nature of local weather patterns as well as dependency on meteorological and plant physiological factors [2]. Several empirical techniques exits for decision support system (DSS) with respect to frost forecasting as reviewed in Ref. [3]. Machine learning approaches is becoming an important tool in agricultural DSS with applications in land preparations, crop management and maintenance, etc [4, 5]. Such approaches have been used to forecast occurrences of frost with a forecasting window of few hours [6–10]. On the other hand, this paper attempts to forecast in a much larger forecasting window on the AoI using ensemble learning.

2 Methods

The Methods section is divided into the following subsections: In subsection 2.1, the definition of frost used in the paper is introduced. It is followed by characterization of forecasting time and window in subsection 2.2. Next, dataset used in this study and its characteristics are presented. The last section deals with the strategy of creating machine learning based models.

2.1 Frost definition

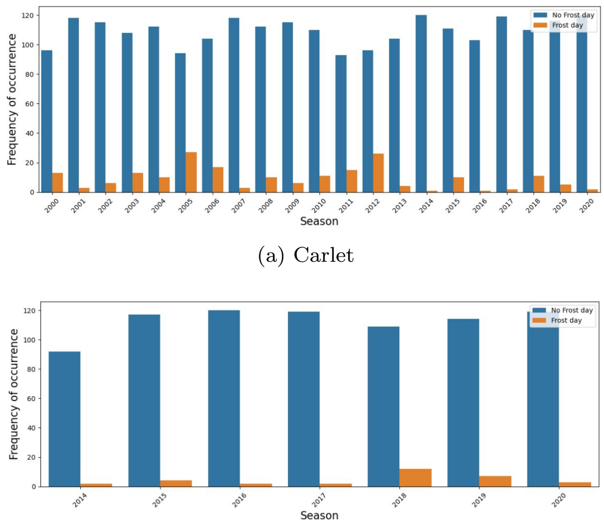
Frost formation occurs when temperature of a surface becomes lower the $0°C$. Formation of frost can occur due incursion of large-scale cold air mass resulting in lowering of temperature below $0°C$. Such event in known as *Advective* frost and can occur during day or night. On the other hand *Radiation* frost is characterized by clear sky, calm or very little wind, inversion of temperature and air temperatures that typically drop below $0°C$. Radiation frosts usually occurs at nigh-time. Both kind of frost generates stress to the agricultural plants and can lead to potential decrease in yield. To define the condition for occurrence of frost on agricultural plants, one need to monitor temperature of plant surfaces. Such a task in clearly not straightforward to carry out. Alternatively, one can use indirect methods to estimate plant temperature using physiological and thermal properties. As a result, in this article, due to constraint on the type of data available at the agro-climatic stations along with lack of ground truth, a frost event is defined if the air temperature becomes lower the $0°C$ within the forecasting window.

2.2 Forecasting window and time

In this paper frost forecasting will done with 24 hour and 48 hour ahead projection. This forecasting window was decided as in the AoI, majority of farmers use anti-frost vitamins like α-tocopherol and glycerol. As described in Ref. [11], such vitamins have to be applied at-least 24-48 hours before to have considerable protection. Additionally, in the present AoI, an agricultural cooperative controls the facilities and resources for providing forst protection to the individual farmers. To prepare adequately, the cooperative needs around 48 hours. So, to give the cooperative time for preparation, the forecasting will be done on each day at noon. Additionally, at Carlet and Belgida, the agronomist in the agricultural cooperative found that during December to March the organic fruits in that area is most susceptible to frost occurrence. As an example, for peaches (Prunus Persica), delicate phenology stages like inflorescence emergence and flowering (BBCH code 55-69) happens within this timescale. As a result we only consider this part of the season for our predictive model.

2.3 Data sources

The weather data was gathered from two agro-climatic stations near Carlet and Belgida. The agro-alimatic station at Carlet is approximately $2-3$ km from the agricultural fields whereas at Belgida the station is located near the agricultural fields. The Carlet station has hourly climate data from 1999 and the Belgida station has the same from 2013. The agro-climatic station data includes the variables Temperature, Wind velocity and direction, Humidity and Precipitation. By defining daily frost events according to 2.1, distribution of frost events at the location of respective agro-climatic stations are shown in Fig. 1. Each season is defined as December to March of the following year. By looking at the distribution of frost events, it is clear that uncharacteristic amount of temperature below $0°C$ was reached for season 2005 and 2012. This is taken into account while creating the training and test dataset. As frost event are usually rare, the dataset is highly imbalanced.



(a) Carlet

(b) Belgida

Figure 1: Distribution of frost days in Belgida and Carlet. Each season consists of December to March.

Data from weather stations directly mounted at the agricultural lands at Carlet and Belgida is used as test dataset for season 2021. Such a dataset though limited in sample size can provide a hint for the performance and generalized nature of the models developed.

2.4 Machine learning models

To create a predictive model, a classification scheme is developed where the target is the presence or absent of frost event in the 24 and 48 hour forecasting window. The strategy is then to employ a type of ensemble machine learning strategy known as *blending* which includes the following steps:

1. The data from agro-climatic stations are divided into three parts: **Training set**: Data until 2010 season, **Holdout set**: Data from 2010 season up to 2014 season, and textbfValidation set: Data from 2010 season up to 2014 season
2. The **Test set** consists of data from weather stations installed at the AoIs for the season 2021
3. Various models are fitted to the data in training set. These are known as *base* models
4. Each of the *base*-models make predictions on the holdout set, validation set and the test set
5. New features are created from the prediction of the base models. A *meta-model* is then trained on these features of the holdout set whose hyper-parameters are optimized with respect to the validation set
6. Predictions are made using the *meta-model* on the base-model features on the test set

Before applying the blending-based based model, different kind of feature engineering was carried out. With each type of engineering method comes with associated different machine learning models as our base-learners. The various approaches is summarized as,

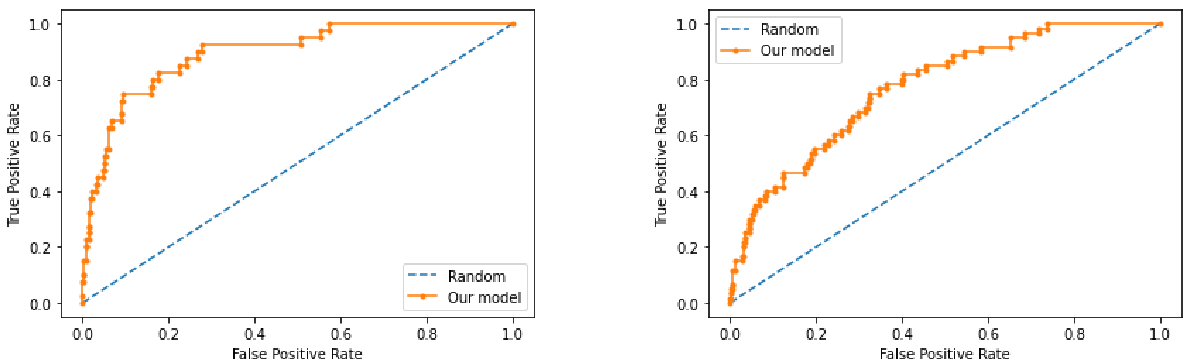
- **Create daily feature**: Daily aggregated features of the variables like temperature, humidity, wind speed and direction etc. Moreover, additional features was created by including past values of such variables. As *base*-learners The algorithms involved are:
  - SVMSMOTE + GBDT: As training data set is highly imbalanced, a synthetic balancing mechanism is used to create minority class data (SVMSMOTE) followed by gradient boosting decision trees (GBDT). A randomized grid search in parameter space was carried out to optimize the outcome.
  - GBDT: GBDT algorithm are used along with adding weights for taking into account the class imbalance. Here also a random search in hyper-parameter space was carried out.
- **Create hourly feature**: Features are developed using shift-invariant wavelet transforms. For each hour of prediction, within a time-window from its past, shift-invariant wavelet transform is applied. This helps to create features which encode information on the long term characteristics of various variables on different time scales. At each scale statistical information was extracted. The resulting dataset is trained using gradient boosting trees.

- **Automatic feature creation using convolutional neural networks**: Within this strategy, the hourly dataset is transformed such that feature selection becomes part of the algorithm. A two-dimensional image is created with one axis being the hours in a day and the other axis representing the number of days in the past for each of the variables present. The transformed dataset is trained with convolutional networks of two different architectures.

- For the *meta-model* Logistic Regression algorithm is used with grid search to find optimized parameters.

2.5 Results

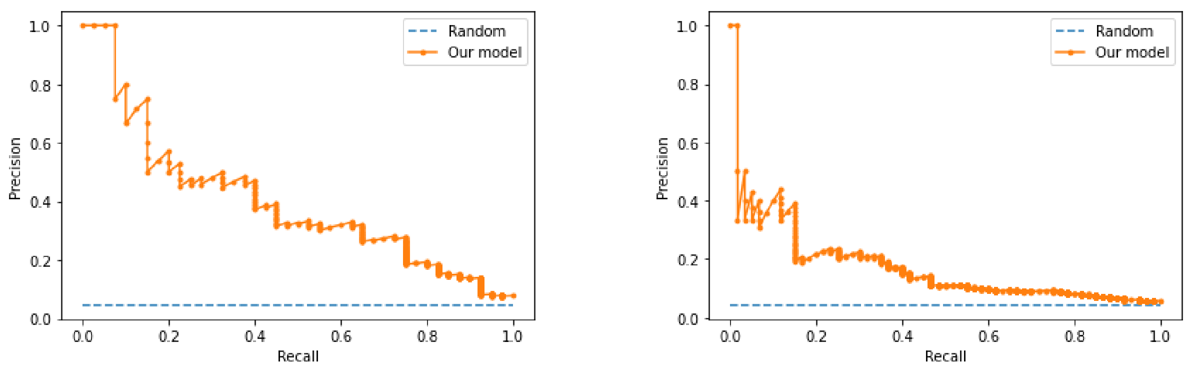
In this section, performance of the final *meta*-model in the validation set is presented. To quantify the performance, the Receiver Operating Characteristic (ROC) curve and the Precision-Recall (PR) curves are used. The ROC curves for 24 and 48 hours forecasting are shown in Figs. 2a, 2b respectively. The solid curves shows the model performance of true positive rate as false positive rate is changed by varying thresholds across the predicted score. The model performs considerably better than a random model (dashed lines) where the prediction is distributed according to the frequency of majority events (no-frost days). Due to the highly unbalanced dataset, PR curves are also created to establish performance against the minority events. The results for 24 and 48 hour forecasting is shown in Fig.3a, 3b respectively. It can be notices that even though the model presented in the paper is better than a minority frequency based random model, in general there is a large trade-off between precision and recall. Moreover, understandably, 48 hour forecasting performs worse than 24 hour ahead prediction as meteorological and climate fluctuations plays a bigger part in 48 hour ahead prediction. It should be noted that sudden changes in the ROC and PR curves are result of smallness of minority class sample size.



(a) 24 hour forecasting

(b) 48 hour forecasting

Figure 2: ROC curves for the model presented in the article for validation dataset.



(a) 24 hour ahead prediction

(b) 48 hour ahead prediction

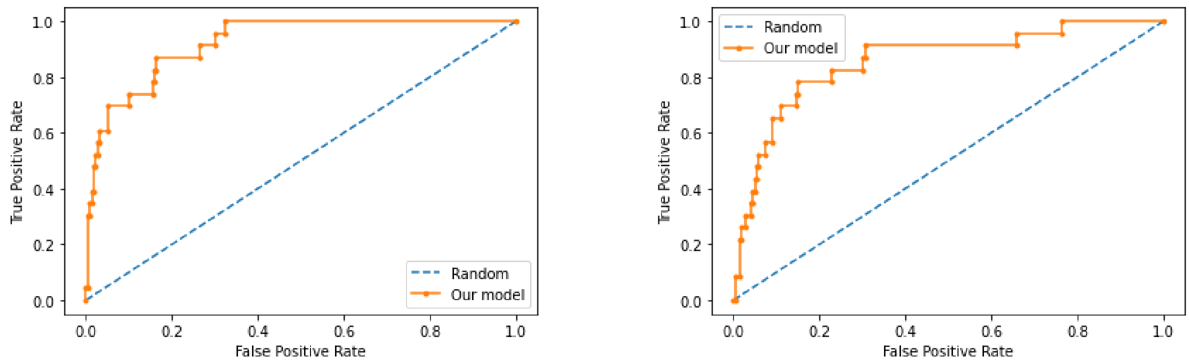
Figure 3: PR curves for the model presented in the article for validation dataset.

Next, model performance is discussed on the test dataset taken from weather stations at the area of interests. By comparing the ROC curves of prediction to test dataset (Fig. 4) to that of validation set

Forecasting	Threshold	Recall	Precision	Balanced Accuracy
24 hour ahead	F2-score	0.87	0.31	0.83
24 hour ahead	J-statistics	0.74	0.39	0.81
48 hour ahead	F2-score	0.83	0.25	0.78
48 hour ahead	J-statistics	0.56	0.45	0.75

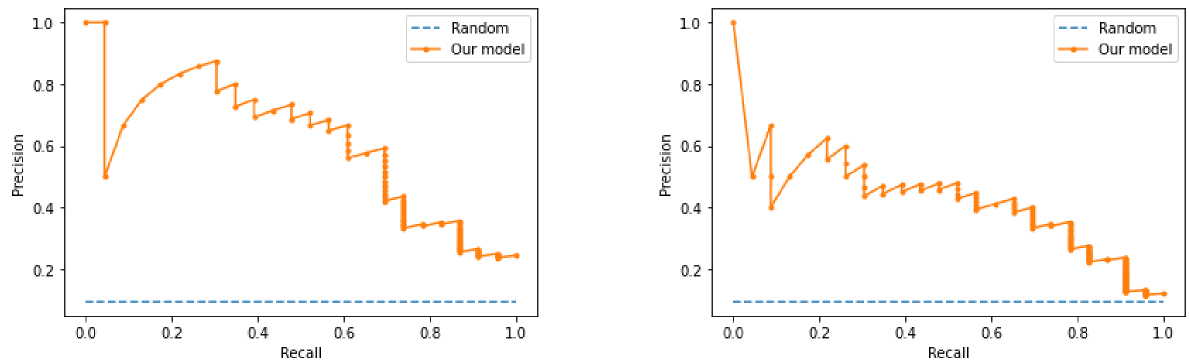
Table 1: Various performance indices for 24 hour and 48 hour ahead predictions based on test dataset.

(Figs.2), it can be seen that the model performances are alike, if not better. Similar conclusion can also be drawn by looking into the PR curves at (Figs.2).



(a) 24 hour forecasting (b) 48 hour forecasting

Figure 4: ROC curves for test dataset



(a) 24 hour ahead prediction (b) 48 hour ahead prediction

Figure 5: PR curves for test dataset.

Similar conclusion can also be drawn by looking into the PR curves at Fig.5. To look into the cases of false positives and false negatives, from the validation set, optimal thresholds are selected by maximizing F_2-score or J-statistics. $F2$-score, instead of more ubiquitous $F1$-score, is considered as recall is more important than precision as failing to predict a frost event can be more costly than having false positives. For each threshold, three different performance indices are considered:
Recall $= \frac{TP}{TP+FN}$, Precision $= \frac{TP}{TP+FP}$, and Balanced Accuracy $= \frac{1}{2}\left[\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right]$, where $TP =$ True Positive, $FP =$ False Positive, $FN =$ True Negative, and $TN =$ True Negative. Under different threshold conditions, the performance indices are shown in Table. 1. As clear from the PR curves, there is a trade-off between precision and recall. As a result, depending on the cost of false positives and type of frost protection measure, one need to decide on thresholds.

3 Conclusion

In conclusion, this paper develops and tests an ensemble-based metamodel for 24 and 48 hour ahead frost prediction using inputs from meteorological stations located in the AoIs.The model performance show a trade-off between precision and recall. In the case of frost prediction, depending on the type of protection measure is taken, eliminating false negatives can be more important than false positives. Hence, recall is given more weight into the performance evaluation. 24 hour ahead prediction is found to be better than the 48 hour one. In future work, a better model can be created by including data from a variety of weather stations near AoIs and also including ground truth data on frost events. Additionally, shifting the forecasting time towards night can lead to better performance as radiative frost in the AoIs happens in early morning. Complimenting the weather data with more variables like evapotranspiration, cloud coverage can also potentially lead to better prediction of frost events.

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