Bulletin of the *Transilvania* University of Brasov
Series II: Forestry • Wood Industry • Agricultural Food Engineering • Vol. 17(66) No. 2 – 2024
https://doi.org/10.31926/but.fwiafe.2024.17.66.2.2

PREDICTING WILLOW PLANTING EVENTS BY CONVENTIONAL MACHINE LEARNING FROM GPS DATA: ACCURACY, GENERALIZATION ABILITY, AND POTENTIAL FOR IMPROVEMENT

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Abstract: *Willow cultivation is an important activity that can provide greater amounts of cleaner and renewable energy. To support the development of this farming sector, data is required on the spatial distribution of planted plots, as well as on the performance of operations typically required in willow crop management. Unfortunately, this kind of data is largely unavailable, while documenting it is a challenging task. GPS data, which may be feasibly collected during operations, may be a good carrier of information not only to document the spatial location of plots, but also to learn about the frequency of typical events as specific to willow operational management. Based on a GPS dataset characterizing two plots, which was collected during planting operations and labelled manually (8,385 observations), a neural network was used in this study to spatially classify events such as driving (hereafter called D), maneuvering (hereafter called M), planting (hereafter called P), and being stopped (hereafter called S). Three models were trained and validated based on features such as GPS speed (hereafter called model S), GPS speed and leg length (hereafter called model S&L), and GPS speed, leg length, and heading (hereafter called model S&L&H), respectively. Classification performance was found to be impressive, with an overall accuracy of 92.0 (S), 92.1 (S&L), and 93.3% (S&L&H), respectively. The quality of the models was then checked visually using a dataset containing unseen data characterizing two plots of different cardinal orientation, indicating an acceptable generalization ability. The methods described in the paper may be useful when dealing with large datasets and limited resources and expertise in labelling the data manually, as they provide location and event specific data with high accuracy. Improvements in accuracy are possible by integrating the raw data in deep learning, an approach that should be explored further.*

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Key words: *willow, cultivation, management, prediction, resources, accuracy, big data, analytics.*

1. Introduction

Concerns about global warming, energy sufficiency and security have shaped many local, national and international policies, emphasizing the need of producing energy sustainably [22, 32]. Short rotation willow represents one of the most valued sources of renewable energy, and it is cultivated in many countries worldwide [3, 13, 20, 25, 27, 41, 48]. To be able to sustain the effort of efficiently producing renewable bioenergy from willow, aggregated data is required on the size of the plots, their spatial distribution, yield, the effects of the rotation period on yield, and performance of the operational management. Typically, this kind of data supports decision-making in several ways, such as having the information required for census purposes, particularly when such data is not available [5], providing incentives to stimulate the practice of farming, and last but not least, evaluating and accounting for the environmental and economic performance of willow management [10, 18, 39].

Despite these benefits, such data is commonly unavailable, particularly data characterizing operational performance, which is a prerequisite for environmental and cost assessment. In short rotation willow management, there are many operations required, starting with establishment and ending with harvesting [19, 46, 47], and the performance of these operations has been commonly assessed by various methods [8, 17, 34, 40, 42, 43]. Since cultivated plots are typically unobstructed, GPS (Global Positioning Data) has been increasingly used to support operational performance studies [7, 9, 12, 21], mainly because it can provide location-specific, accurate spatial data which can be then classified by the human eye to extract useful information. In addition, GPS receivers have become cost-affordable, while the consumer-grade ones can provide reliable data on several parameters such as location and speed of movement [6, 28, 30]. While these features make them valuable tools in collecting the necessary data, the classification of events still requires dedicated human expertise and resources which are not largely available and may be prone to error.

Conventional machine learning could be one of the solutions to classify the operational events based on GPS data. This is because operational events are typically researched in time studies some of which include classification problems [2, 44]. Accordingly, operational management of willow grown in short rotation coppice could benefit to a large extent from integrating GPS data with machine learning, due to some specific spatial features of the operational events, such as their development on relatively linear trajectories, a repetition pattern which is similar, a shape of the plots which is typically a simple geometrical feature such as a rectangle, and a relatively constant speed when operating. In terms of GPS data, these features can be measured in terms of speed, heading, and distances between the collected locations. Then they can be labelled and fed into machine learning algorithms such as neural networks to learn specific patterns and make predictions on unseen data.

While the learning process can be intensive in regards to computational resources, the benefits that one may account for are promising since the developed models may be used to classify in a short time very large datasets lacking classification labels.

Willow planting is one of the very first steps in the operational management of willow short rotation crops which, by GPS data collection, can provide the spatial context of the cultivated plots. In addition, at the level of the technical development implemented in practice, willow planting is still a partly mechanized process, typically requiring a machine that acts as a carrier and manual labor for the effective planting operation [7, 12, 34, 44]. The goal of this study was to check the degree to which GPS data can be used along with conventional machine learning to document and predict the operational events in willow planting operations. The first objective of the study was to train and validate a set of neural models able to recognize and predict the typical events in willow planting operations based on GPS features such as speed, distance between locations, and heading. The second objective of the study was to subjectively check the performance of the developed models on unlabelled data showing a variety in events and geometrical GPS features.

2. Materials and Methods

2.1. Study Location, Description of Operational Events, and Data Collection

The data supporting this study was collected in the center of Romania (Figure 1), in the counties of Brasov and Covasna. Although willow farming is typical to the whole country, the center of Romania has more tradition with such crops, with important areas established with willow over time [5]. The climate of the area is also favorable for willow cultivation; however, the size of the plots is rather small, and they are typically spatially dispersed.

Fig. 1. *Study Location. Legend: the green dot indicates the location of the first dataset (D1), while the red dot indicates the location of the second dataset (D2)*

Two datasets were collected and used in this study. A first dataset (hereafter called D1) was collected near the village of Tărlungeni, Brasov County, and it was used for the training and validation of the neural network models. It featured a number of 8,385 data points collected at a rate of five seconds by a consumer-grade GPS receiver placed on the cab of a tractor used as a carrier for planting. The second dataset (hereafter called D2) was collected near the village of Poian, Covasna County, and it was used for the visual assessment of the generalization ability of the developed neural network models. It featured a number of 43,594 datapoints collected at a rate of one second. Both D1 and D2 covered two planted plots each, as well as the typical events in willow planting described in Table 1. The difference between the datasets was in regards to plot orientation, as well as the relative distribution of events in the data.

Table 1

Typical events in willow planting operations by the machine and work team used

Event	Abbreviation	Description
Driving	D	Moving the machine between planting locations, from the garage to a planting location, or from the last planted location to the garage. It also includes movements within the plot and it is typically done at higher speeds compared to the rest of the events.
Maneuvering	M	Maneuvers taken at the headlands to exit or enter a planting row, as well as in the plot to avoid potential obstacles.
Planting	P	Effective planting consisting of machine movement along a straight path while the workers insert the cuttings into the soil; movement is typically done at low and constant speed to allow the workers to keep the planting pace.
Stopped	S	Various events in the plot or at the headland during which the machine does not move.

While there are several technical options used to plant willow, one is dominant in Romania. It consists of a farm tractor equipped with a wheeled aggregate designed to carry the workers and the willow cuttings that are manually inserted into the soil during the actual planting. The machine works in legs by entering the plot, driving in a straight line at low speed while the workers insert the cuttings manually into the soil, exits a given planted row, and takes maneuvers to re-enter the plot. When the operations in a given plot are finished, the machine drives to a new location to be planted. Driving may also occur within a given plot to accommodate the planting when the plots are not rectangular. All of these events are intercalated with stops caused by various reasons. A detailed description of the machine and way of working can be found in [7, 44].

The typical planting work includes effective planting, maneuvering, driving between plots, and events in which the machine is stopped. Although the machine and methods used are different to those from other parts of the world, the typical operational events are similar [7, 12, 34, 44]. By continuous recording in the tracking mode, GPS data provides the context of spatial location in terms of coordinates. The data comes along with other important features such as movement speed, heading, and distance between the collected locations.

2.2. Data Preprocessing and Machine Learning

Data from D1 and D2 was saved as GPX files and imported in two Microsoft Excel (www.microsoft.com, accessed on 1 September 2024) files via Garmin Basecamp (www.garmin.com/en-US/software/basecamp/, accessed on 1 September 2024) software. Garmin Basecamp software enables the estimation of movement speed, distance between the collected locations, and heading, among other features such as elevation and geographical coordinates. D1 was checked in detail in Garmin Basecamp and labelled point by point in a Microsoft Excel database by string codes designating the events described in Table 1. Data labelling was based on the location geometry and movement speed, along with the expertise over the events gained during the field observations.

Machine learning was implemented in Orange Visual Programming software [16], where D1 was imported and a neural network in the form of a single layer perceptron with backpropagation was implemented as a final training and validation attempt. The specifications of the neural network hyperparameters and their function in the performance of the neural network are described for instance, in [36]. Several tests designed to check the classification performance were implemented by varying the number of layers, the number of neurons in the hidden layers, and the regularization parameter. These were carried out to see what would be the best architecture of the model, as well as to tune the regularization parameter. At the end, a neural network with a single layer of 100 neurons, trained with a regularization parameter of 0.0001 in 1,000,000 iterations using the RELU activation function [1, 33, 35] and the ADAM solver [31] was found to be the best option in terms of classification performance when feeding the network successively with up to three features: speed (hereafter called model S), speed and distance between locations (hereafter called model S&L), and speed, distance between locations, and heading (hereafter called model S&L&H). A training and validating procedure that involved cross validation by five folds was used to check the performance of the three models in this step. Classification performance was evaluated by using classification accuracy (CA) as a metric. However, other common metrics of classification performance such as the area under receiver operating curve (AUC), F1 score (F1), precision (PREC), recall (REC), and cross entropy (LOSS) were estimated as well at event and overall level. Definitions for most of these metrics can be found, for instance, in [23, 26]. The machine learning algorithm used has the ability to treat the magnitude in values by standardization of the data [37], therefore such a scaling technique can accommodate to some extent the variability in features, thus removing the bias of the models towards larger values [38]. In addition, metrics such as precision, recall, and F1 score can be more appropriate when dealing with class imbalance [45].

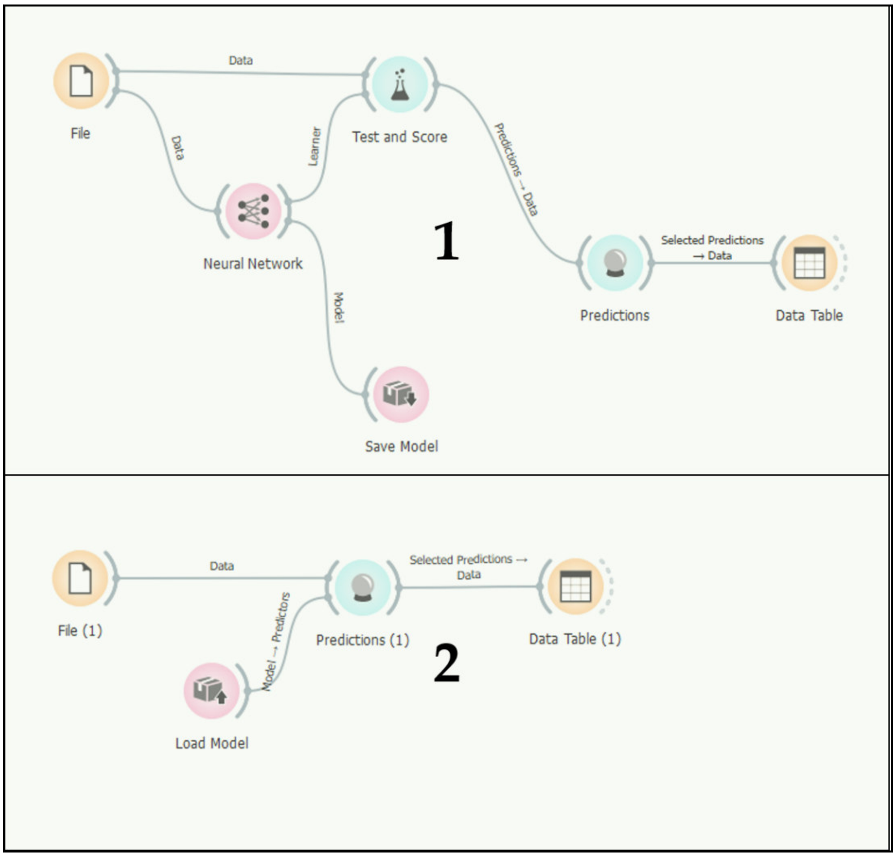


Fig. 2. *Workflows used in Orange Visual Programming software to train and validate the models on D1 (1) and to test the models on D2 (2). Legend: the file widget connects to a database stored in Microsoft Excel format and allows for the selection of feature and target variables, the Neural Network widget allows for tuning of the network, training and validating the models, the Test and Score widget allows for the estimation of relevant classification performance metrics, the Save Model widget enables model saving, the Predictions widget enables predictions made by the model, the Data Table widget enables data manipulation, and the Load Model widget enables loading a model from the location in which it was saved*

The developed neural network models were saved and tested over the unlabelled data with the aim of visually checking their performance. In both machine learning steps, maps were produced in QGis (version 2.18) based on the GPX files that were joined with the Microsoft Excel data. For the first step (training and validation), classification performance was reported as tabulated data for all the metrics, while the classification accuracy was (CA) graphically compared between the models at the event and overall levels. Classification made by the human labeler was developed in the form of a map of GPS locations, and it was reported along with the maps of the misclassifications made by the three machine learning models.

For the second step, the predictions made by the models were associated to the spatial data of the GPX file to visually assess their accuracy. Although this was done for two plots in each step, for simplicity of visualization this study reports on a single plot example in the first step and for two plot examples in the second step. To design, train, validate and test the neural networks, the widgets "File", "Neural Network", "Test & score", "Save Model", "Load Model", "Predictions", and "Data Table" of the Orange Visual Programming software (Widget catalog, available at: https://orangedatamining.com/widget-catalog/, accessed on 3 September, 2024) were used in purposely developed workflows (Figure 2). After training and validating the models, the Excel database of D1 dataset was updated with the necessary information related to the predictions made by the models. Based on these, misclassifications were detected and added as new attributes in the database, which was connected to the QGis GPX data for mapping purposes.

Once the models were used to make predictions on D2, their predictions were saved in the Microsoft Excel database as new attributes provided as string codes. An updated version of the database was then connected to its corresponding GPX file in QGis and used to map the predictions made by the three models on the unseen data of D2.

3. Results

3.1. Description of Data

D1 contained 8,385 datapoints (Table 2), and showed a high-class imbalance, where the "Planting" event dominated the dataset by close to 67% of the data, while the "Stopped" event accounted almost for the rest of the data (26%). While the data on the "Heading" feature showed a limited variability due to the geometry of the plot, the data on speed was rather heterogeneous in nature, indicating the type of events labelled by the human expert. Figure 3 shows a classification of the data from D1 (a plot given as example) based on GPS speed and natural breaks rule, where the color intensity denotes the magnitude in speed from lower to higher.

In terms of speed, the operational events were heterogeneous. "Planting" had a lower variability in speed, which was close to 1.2 km/h, "Maneuvering" had a higher variability in speed, and "Driving" by was characterized by speeds that commonly exceeded 4 km/h.

Table 2

Frequency of events in D1

Event	Abbreviation	Absolute frequency	Relative frequency [%]
Overall	O	8,385	100
Driving	D	168	2
Maneuvering	M	461	5
Planting	P	5,586	67
Stopped	S	2,170	26

Fig. 3. *GPS speed classification in QGis based on data from D1: an example for a planted plot using natural breaks as a classification rule. Note: the map is rotated 90 degrees to the right*

3.2. Classification Performance

Classification performance was high for all the models. For instance, classification accuracy achieved values of 92 to 93.3% (Figure 4), with events such as "Driving" being characterized by excellent classification performances (99.1%). Overall, the "Stopped" events were clearly identified by the machine learning algorithms, returning classification accuracies of 96 to 96.5%. This was due to their low, constant speed. Although "Planting" and "Maneuvering" returned high and similar classification accuracies, their classification performance was likely influenced by variability at least in speed and inter-point distance; for these events, classification accuracy was from 94.5 to 95.9%.

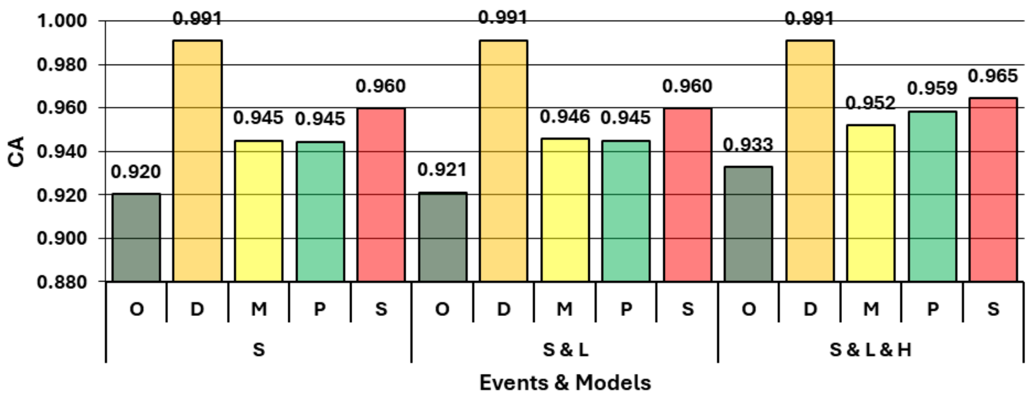


Fig. 4. *Classification accuracy compared between the three neural network models (S, S&L, S&L&H) at event level. Legend: O – overall, D – driving, M – maneuvering, P – planting, S – stopped*

The use of inter-point distance improved only marginally (0.1%) the overall classification accuracy of the model. However, using the inter-point distance and heading in addition to the GPS speed improved to a higher extent the overall classification accuracy of the model (1.3%), as shown in Figure 4. These improvements seem to come from a particular improvement in classification over the M, P, and S events, since the performance in classifying the D event was the same, irrespective of the model. Figure 5 shows the misclassifications of the models against the ground truth labelled by the human expert by considering a single plot taken as an example, and by indicating two important things.

First, the localization of the misclassifications seemed to be similar, irrespective of the model used to make predictions. These were located in those areas in which maneuvering took place dominantly (i.e., at the headlands). Secondly, the model S&L&H performed better, showing fewer misclassifications, while the models S&L and S, respectively, seemed to have a similar behavior in misclassifying the data. In addition, Table 3 gives an overview on the event-based classification performance metrics for the three models. In particular, the data showed an excellent recall (REC) for the “Planting” and “Stopped” events which were the highest for the S model, while recall stands for the correctly identified true positive examples from all true positive data.

Table 3

Summary of the event-based classification performance metrics of the three neural network models

Model	Event (Abbreviation)	AUC	CA	F1	PREC	REC	LOSS
S & L & H	Overall (O)	0.950	0.920	0.903	0.902	0.920	0.276
	Driving (D)	0.964	0.991	0.758	0.815	0.708	0.031
	Maneuvering (M)	0.760	0.945	0.176	0.505	0.106	0.182
	Planting (P)	0.964	0.945	0.959	0.938	0.982	0.174
	Stopped (S)	0.986	0.960	0.925	0.900	0.951	0.116
S & L	Overall (O)	0.950	0.921	0.905	0.904	0.921	0.276
	Driving (D)	0.962	0.991	0.767	0.828	0.714	0.031
	Maneuvering (M)	0.761	0.946	0.201	0.533	0.124	0.182
	Planting (P)	0.965	0.945	0.960	0.939	0.982	0.175
	Stopped (S)	0.986	0.960	0.925	0.900	0.951	0.116
S	Overall (O)	0.973	0.933	0.923	0.923	0.933	0.229
	Driving (D)	0.970	0.991	0.755	0.824	0.696	0.030
	Maneuvering (M)	0.873	0.952	0.374	0.663	0.260	0.148
	Planting (P)	0.985	0.959	0.970	0.952	0.988	0.127
	Stopped (S)	0.988	0.965	0.933	0.914	0.953	0.109

Note: AUC stands for the area under the receiver operating curve, CA – classification accuracy, F1 – F1 score, PREC – precision, REC – recall, LOSS – cross entropy

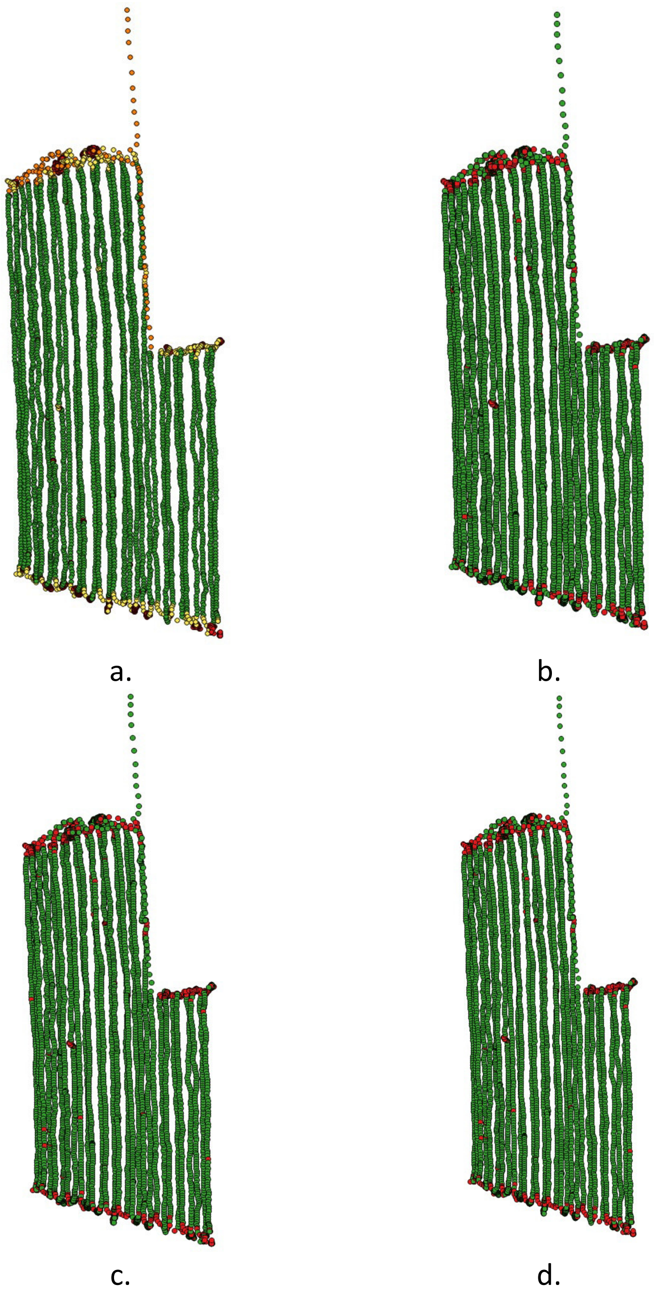


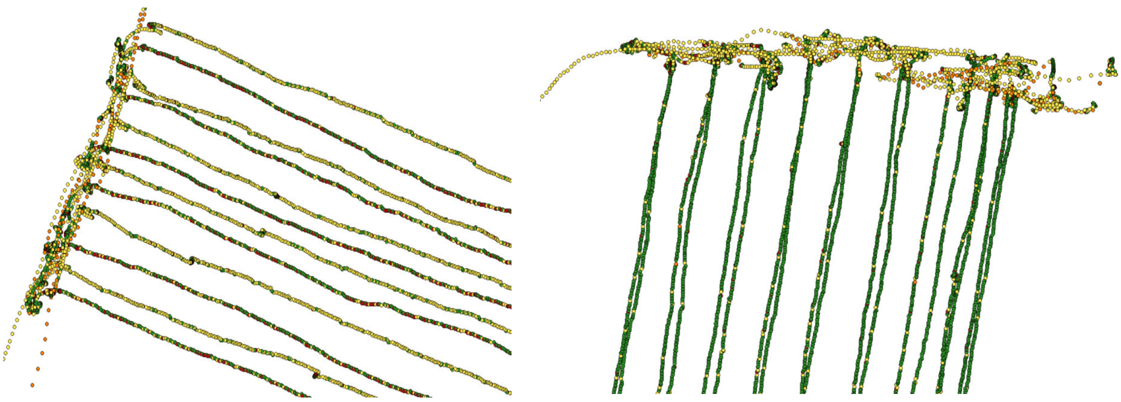
Fig. 5. *Misclassifications of the models against the data labelled by the human expert. An example for a plot from D1: a. data as it was labelled by the human expert; b. misclassifications of the S&L&H model; c. misclassifications of the S&L model; d. misclassifications of the S model. Legend: in panel (a.) green stands for "Planting", yellow for "Maneuvering", orange for "Driving", and red for "Stopped" as the ground truth; in panels (b.) to (d.) red stands for misclassifications*

3.3. Models' Predictions of Unseen Data

Figures 6 to 8 give examples on the performance of the three models (S&L&H – Figure 6, S&L – Figure 7, and S – Figure 8) on two plots which were different in terms of event heading data. The S&L&H model tended to correctly classify the data from that plot which had a similar heading of events. For instance, "Planting" was generally well classified (Figure 6), although some "Maneuvering" events were placed within the plot and some of the "Stopped" events were confused with "Planting".

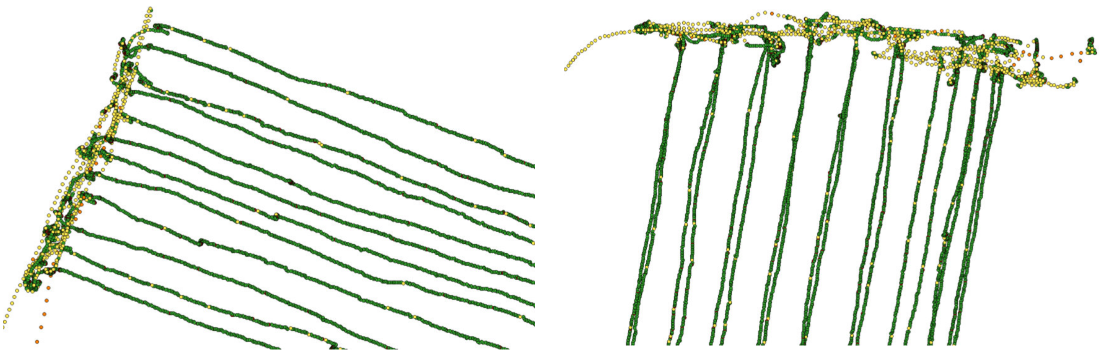
In turn, the plot characterized by a different heading data as compared to that used for training and validation showed a higher number of misclassifications (Figure 6a). This points out that the inclusion of heading in the models may bring some important limitations even though the models use preprocessed data. Figure 7 shows some examples on how the S&L model performed on the same data.

Given the geometry of the points, it is evident that prediction of the "Planting" event improved in the first example (Figure 7a), while it remained quite unchanged (although good) in the second example (Figure 7b). However, the "Driving" events seemed to be misclassified as "Maneuvering" in both examples. Only a small part of the data remained classified as "Driving" even for the plot example that was similar in geometry to the one used to train the model. Accordingly, the limitation of the model was that related to misclassifying the events which ran at higher speeds. Finally, Figure 7 shows some examples on how the S model performed on the same data.



a. b.

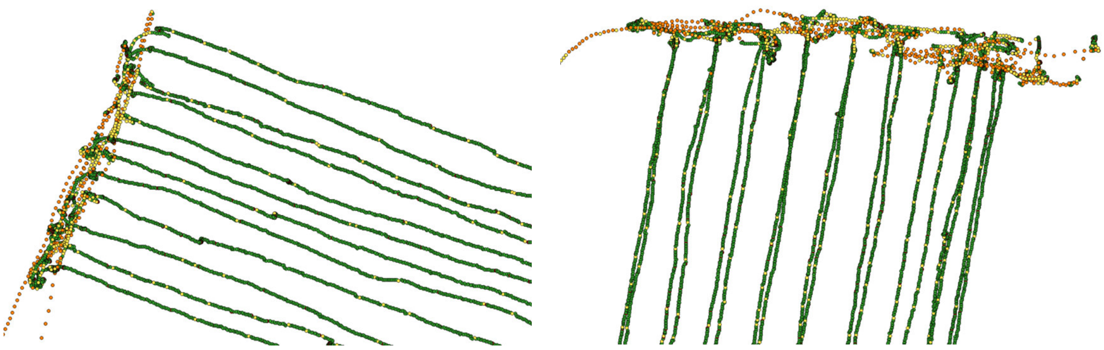
Fig. 6. *Examples of predictions made by the S&L&H model on two plots: a. plot with a different heading on the events compared to those of D1; b. plot similar in geometry with that of D1. Legend: green stands for "Planting", yellow for "Maneuvering", orange for "Driving", and red for "Stopped" as predicted on the model on unseen data*



a. b.

Fig. 7. *Examples of predictions made by the S&L model on two plots: a. plot with a different heading on the events compared to those of D1; b. plot similar in geometry with that of D1. Legend: green stands for "Planting", yellow for "Maneuvering", orange for "Driving", and red for "Stopped" as predicted on the model on unseen data*

The "Planting" event remained predicted in a way that was similar to what S&L can do. In addition, prediction of the "Driving" events improved and was delimited more clearly from "Maneuvering", irrespective of the general geometry of the plot. As such, for the unseen data, the model based on GPS speed seemed to perform the best. This may be explained if one rechecks Figure 5 showing that in the training and validation phase the models differed only to a small extent in terms of misclassification, with these misclassifications being more related to the "Maneuvering" events.



a. b.

Fig. 8. *Examples of predictions made by the S model on two plots: a. plot with a different heading on the events compared to those of D1; b. plot similar in geometry with that of D1. Legend: green stands for "Planting", yellow for "Maneuvering", orange for "Driving" and red for "Stopped" as predicted on the model on unseen data*

4. Discussion

As found in this study, integrating GPS data into conventional machine learning models may help to successfully and accurately detect operational events in willow planting operations, which can sustain the informed decisions based on large amounts of data. Such data can be procured in a relatively inexpensive way, and would be helpful to understand the operational events and to have an updated database of the established plots. These features are of particular importance when such plots are small in size and spatially dispersed [5, 44], which makes it difficult to keep track of willow farming areas.

The human eye can make a good classification of the events based on previous knowledge, the spatial architecture of the GPS locations and other features such as moving speed. However, humans have a limited ability to work with and annotate large datasets without error. The results of this study indicate that GPS data and conventional machine learning may help in overcoming this limitation since classification performance was very high, exceeding 90%. In a highly unbalanced dataset such as that from D1, recall was also higher for the most important events such as "Planting" and "Stopped". The ability to automatically detect movement from non-movement data points is important since other events that take place at the headlands and on dirt roads may be easily identified and classified based on other geospatial features. In other words, what happens in the plot can be accurately detected based on GPS features such as speed, inter-point distance, and heading.

However, not all of these models had a good generalization ability. This is because the heading feature, for instance, will return plot specific values for a given event, varying in a rather limited range for that event. For example, planting on a north-south direction will, in theory, return headings close to 0 and 360 degrees, assuming that the datapoints follow a linear trajectory. It seems that conventional machine learning models such as neural networks have a limited ability to remove this bias, even though they preprocess the data by standardization. One solution to this problem will be labelling larger amounts of data to capture the variability in heading (and other features). This would not only take important resources, but will also question the availability of such spatial configurations of the data points, while it will bring at least intra-class similarity in features [11, 14], which can be a difficult problem to overcome. Another solution would be using statistical descriptors and kernels to preprocess the data [4, 29], since these techniques would be able to extract better features of central tendency and dispersion, providing some degree of invariance (stability) as opposed to the instant readings by the sensors, which was the approach that was taken in this study. Extracting these derived features would not be computationally intensive, but they would require additional data processing steps.

Last but not least, deep learning could remove many of these inconveniences and will potentially increase classification performance. This is because deep neural network models are able to learn more complex features [24], while there are already deep learning networks able to accommodate time series data, which is a typical case of activity recognition, such as the Recurrent Neural Networks (RNNs) [15]. This class of networks use sequential feeding, while their input consists of the current data and previous examples. Subtypes of such networks are Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional RNNs [15]. Typically, these types of networks require specialized software for annotation which can also work on 1D channel data such as GPS speed, heading, and inter-point distances, and it is likely that they would better capture the complexity in data, a reason for which further studies could check their performance.

5. Conclusions

Integration of GPS data in conventional machine learning models provides a useful and easy-to-use tool for operational monitoring in willow planting operations. Once the models based on GPS features are sufficiently accurate in the training and validation steps, they can be easily deployed in an offline approach to classify such events for large datasets. However, this approach still requires some programming to extract the numerical features out of text strings produced by the software used, as well as an offline (although free) approach as in this study. While some of these gaps can be bridged programmatically, future studies could check the additional potential power and utility of deep learning techniques in classifying operational events, as well as the potential of developing dedicated tools based on deep learning models.

Acknowledgements

The Authors acknowledges the support of the Department of Forest Engineering, Forest Management Planning and Terrestrial Measurements, the Faculty of Silviculture and Forest Engineering, Transilvania University of Brasov, for providing the equipment required to collect, process and analyze the data. The Authors would like to thank Dr. Marius Cheţa and Dr. Nicolae Talagai for helping with field data collection.

Funding

This work was supported by two grants of the Romanian Ministry of Education and Research, CNCS – UEFISCDI, project number PN-IV-P8-8.1-PRE-HE-ORG-2023-0141, and project number PN-IV-P8-8.1-PRE-HE-ORG-2024-0186, within PNCDI IV.

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