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Forecasting critical weather front transitions based on locally measured meteorological data

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Abstract— Certain types of medical meteorological phenomenontransitions can have a significant deteriorating effect on road safety conditions. Hence, a system that is capable of warning road users of the possibility of such conversions can prove to be utterly useful. Vehicles on different levels of automation (i.e., ones equipped with driver assistance systems – DAS) can use this information to adjust their parameters and become more cautious or warn the drivers to be more careful while driving. In this paper, we prove that identifying the critical type of weather front transition (i.e., no front to unstable cold front) is possible based on locally observable meteorological information. We present our method for classifying weather front transitions to non-critical versus critical types. Our developed machine learning model was trained on a dataset covering 10 years of meteorological data in Hungary, and it shows promising results with a recall value of 86%, and an F1-score of 60%.

As the developed method will form the basis of a patent, we are omitting key components and parameters of our solution from this paper.

Key-words: weather front prediction, machine learning, crowdsourcing, local weather and weather fronts, road safety

1. Introduction

In recent years, autonomous vehicle technology has seen an unprecedented scrutiny. However, full self-driving vehicles have still yet to take over the public roads in most parts of the world. The levels of vehicle autonomy is described in *SAE J3016* (2014). On lower levels lie cars with less complex automation features, i.e., driver assistance systems and advanced driver assistance systems. A very important feature of such vehicles is the capability to improve their navigation or at least give instructions to their human drivers – or intervene in some well justifiable cases above level 1 of the six levels of vehicle autonomy.

One key component of driving safety comes from the steady vigilance of the drivers. This ensures that if necessary, the driver is capable of successfully maneuvering unexpected and dangerous road situations. Bad environmental conditions often require the drivers to be more focused. A solution that is capable of warning drivers of the presence of traffic-influencing circumstances are therefore an essential part of modern driving assistance systems, self driving vehicles, and traffic management solutions.

Weather conditions and especially weather front transitions can negatively effect the vigilance of road users, and thus, they are a fundamental consideration for designing such a system. Learning the current (daily) medical meteorological phenomena can currently be accomplished by receiving outputs from expert analyses. This is often not readily available for public use and can be significantly delayed compared to the timing expectations of a low latency traffic management system.

In this paper we present (i) our dataset that was used for training and (ii) a novel machine learning (ML) solution that is capable of yielding suggestions for critical medical meteorological transitions. The paper is constructed as follows: In Section 4.1 we introduce the scientific background of our research. Then in section 2 we present the used datasets and the methods employed in our classification solution. We showcase our results in section 3, then discuss those in section 4 giving an outlook to our future aims in this subject in subsection 4.1.

1.1. Previous work

Weather conditions have a significant direct effect on traffic safety. This is predominantly caused by the effect that precipitation and temperature changes have on visibility and the friction properties of vehicles' tyres and the road surfaces (*Andrey* et al., 2001; *Becker* et al., 2022). Previous research has also argued that medical meteorological conditions also have an indirect negative effect on the frequency of road accidents through negatively influencing humans' vigilance (*Örményi*, 1975).

In our previous work (*Szántó* and *Vajta*, 2019b), we designed a statistical analysis for the inspection of whether this decrease in driver vigilance causes growth in road accidents. For this, we analysed different front transition types in Hungary:

- no front to unstable cold front;
- no front to stable cold front;
- no front to stable warm front;
- no front to unstable warm front;
- unstable cold front to no front;
- stable warm front to no front;
- unstable warm front to unstable cold front;
- stable cold front to unstable cold front.

We successfully showed that there was a significant connection between the transition from no front to unstable cold front, the number of road accidents increased both within and outside city limits in Hungary for the analysed time window, i.e., January 1, 2001–December 31, 2010. In that work, we also proposed an algorithm that allows for information related to medical meteorological phenomenon transitions to be yielded from local meteorological measurements. For this, we proposed a hand-crafted algorithm, whose parameters were tuned empirically in order to effectively suggest a flag that corresponds to the presence of an unstable cold front.

In our previous paper (*Szántó* and *Vajta,* 2019b), we also suggested that such a hazard attribute can be used in an intelligent traffic control system that is capable of warning vehicle operators (autonomous agents or humans) of worsened traffic safety conditions. A framework that is capable of hosting such information is introduced in (*Szántó* and *Vajta,* 2019a). A similar solution is proposed by *Kavas-Torris et al*. (2021), wherein the authors define a system for vehicles connected to a network that offers information of environmental information gathered by an unmanned aerial vehicle (UAV). Among others, the broadcast information includes data on weather fronts.

The usage of ML techniques for the prediction of weather circumstances have seen interest in the last few years (*Singh et al.*, 2019; *Dadhich et al.*, 2021). Binary weather classification problems, such as the one described in this article, have also been studied in depth across the scientific community (*Balamurugan* and *Manojkumar,* 2021). However, to the best of our knowledge, no previous solution focused on the usage ML-based classification of weather front transitions.

2. Data and methods

In this section, we describe the dataset on which our analysis is based, and give an introduction to the methods used during the design of our solution.

2.1. Dataset

As one of the main goals of our research was to find possible connections between local meteorological data and weather front transitions, we used a dataset containing information collected at local meteorological stations in Hungary. The same dataset was previously utilized in *Szántó* and *Vajta* (2019b). For front types, we have obtained medical meteorological phenomena that were recorded on a daily basis for the time period between January 1, 2001 and December 31, 2010. This set of data was supplied by the Data Supply Department of the Hungarian Meteorological Service. The second part of our utilized dataset consists of daily accumulated measurements for selected meteorological observatory sites of the Hungarian Meteorological Service (Budapest, Pécs, Szeged, Debrecen, Szombathely, Győr, Nagykanizsa, and Siófok).

Note that the original local weather dataset that was used in *Vécsei* and *Kovács* (2014) had an hourly resolution, but since we only managed to obtain weather fronts recorded on a daily basis, we accumulated the datapoints. Originally, the local weather dataset contained information for the time period between January 1, 1990 and December 31, 2010. However, for the purpose of the study presented in this paper, we could not make use of measurements taken prior to January 1, 1990, therefore, we cropped the dataset to only contain information starting from this date.

As the feature-set for our ML-based classifier, we used local weather measurements with a few additional derived features. For the previously listed cities, the complete set contains daily average temperature, daily average wind speed, daily average atmospheric pressure, and total precipitation, as well as the variation of the respective values from the previous day. The feature-set also contains one-hot encoded precipitation types for the given days. Additional geographical daily mean temperature differences were calculated between selected city-pairs. Sign of the differences has been decided based on the geographical location of the compared cities. The construction of these features has been described in more depth in our previous paper (*Szántó* and *Vajta,* 2019b).

As our previous results showed, the most critical front transition is from no front to unstable cold front state. Therefore we created a binary target variable whose values relate to this change dynamic:

– The value of 0 (or False) corresponds with no front transition or no critical front transition;
– The value of 1 (or True) corresponds with the critical front transition.

This categorization gave us a strongly unbalanced target variable. The empirical distribution of our target variable is shown in *Fig. 1*.

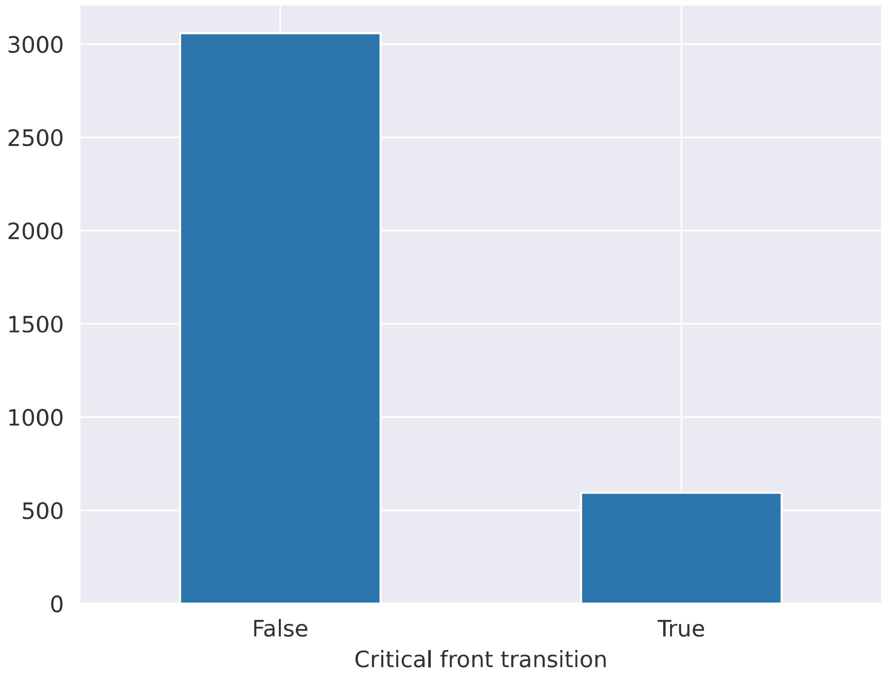
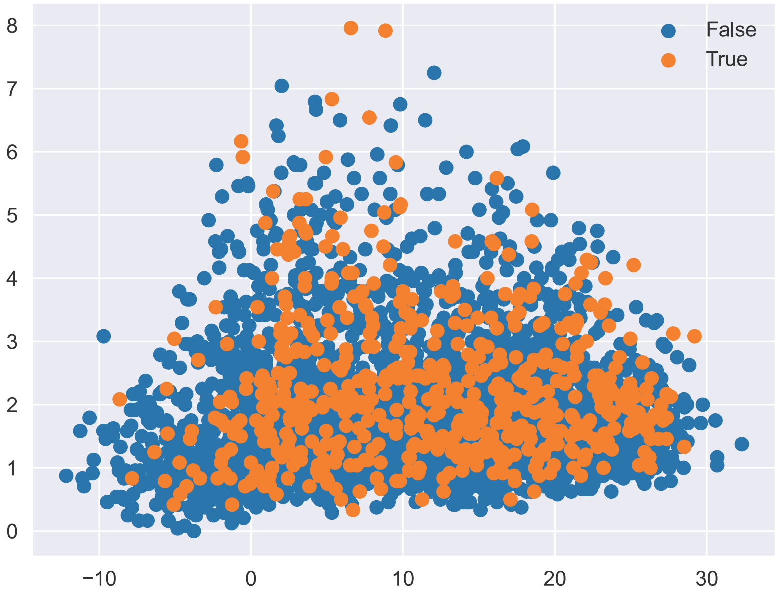


Fig. 1. Heavily unbalanced target distribution. The vertical axis shows the number of transitions. True label denotes critical front transition, while False label denotes no critical front transition.

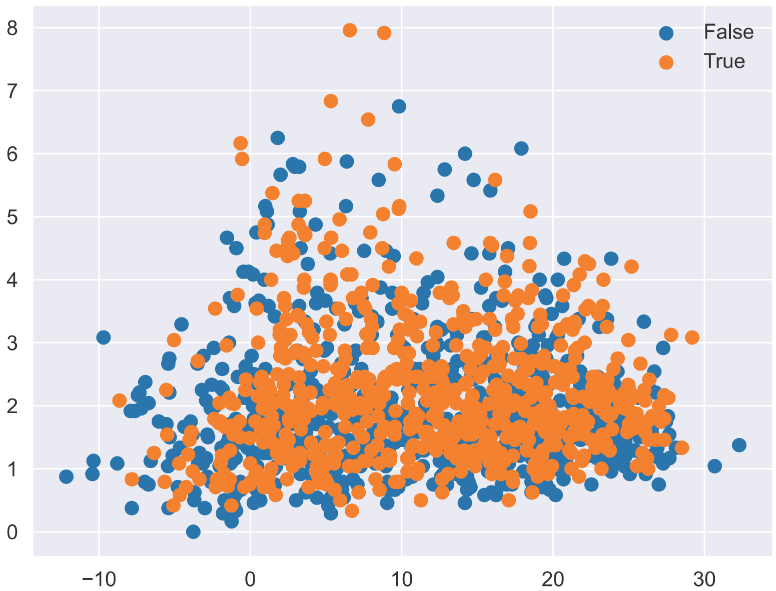
2.2. Methods

The resulting method presented in this report is used as the basis for a patent filing. Therefore, many steps of the data preprocessing pipeline, as well as the type and parameters of the trained ML algorithm are omitted from this publication.

First, we randomly split the dataset into training and test subsets. We did so using a 90% to 10% ratio. The heavily unbalanced target variable (as shown in *Fig. 1*) made data augmentation a necessity prior to model training. For this purpose, we randomly oversampled and undersampled the respective portions of the training set (*Branco et al.,* 2016). The result of resampling is shown in *Fig. 2*. The distribution of the target variable in the training split following resampling is shown in *Fig. 3*.



(a)



(b)

Fig. 2. Data distribution before (a) and after (b) data augmentation. The vertical and horizontal axes show randomly chosen features. True label denotes critical front transition, while False label denotes no critical front transition.

For binary classification, we used three different approaches:

– a traditional ML technique;

– an Artificial Neural Network-based (ANN) technique; and

– a recently published ML technique that makes use of decision trees and boosting.

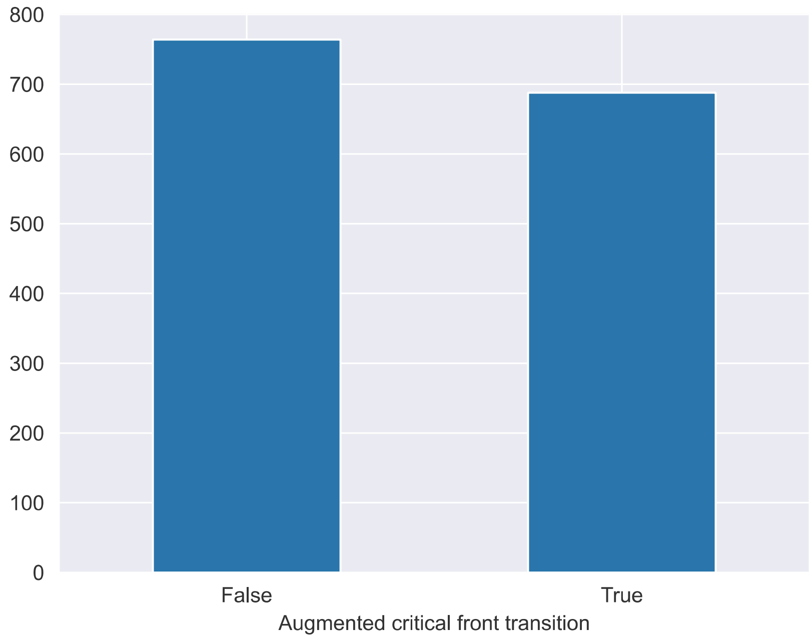


Fig. 3. Augmented training data – target distribution. The vertical axis shows the number of transitions. True label denotes critical front transition, while False label denotes no critical front transition.

In the interest of safeguarding intellectual property rights, technical details are intentionally omitted from this paper, as they constitute foundational aspects of a forthcoming patent application. Therefore, in the following sections of the paper, these will be denoted as Method 1, Method 2, and Method 3.

Method 1 is a decision tree-based multi-class classification ensemble model. The approach used in this paper was proposed in the paper of *Geurts* et al. (2006). We chose this technique, as – similarly to random forest classifiers – it trains multiple decision trees on the training data, but it does not use bagging, and thus, it is less resource-sensitive, while also less prone to overfitting.

For fitting the extra trees classifier, we used the Gini impurity to measure the quality of each split, with minimum 2 samples used to split an internal node. The model was allowed to use at most 12 features to create a split.

We empirically tuned two hyperparameters of the model (number of estimators fitted and minimum number of samples at leaf) as shown in *Table 1*. For comparing the results of the individual models, we used k-fold cross-validation and calculated the test R2 scores.

Method 2 is a fully connected neural network with a depth of 4. It employs dense layers with different activation functions used in the feed forward connections. The simplified structure of the used ANN is shown in *Fig. 4*.

For the hidden layers – l_1 to l_4 in *Fig. 4* – , the rectified linear unit (ReLU) (*Nair* and *Hinton,* 2010) activation function was used, whereas in the case of the final connection – l_4 to l_O in *Fig. 4* –, we employed the softmax function that yields probability values for the individual output classes. For the outputs of every hidden layer, we used batch normalization. We aided the optimization process with learning rate (LR) scheduling; namely, we used step LR decay, which iteratively applies a division to the learning rate by a prescribed factor (γ) after a given number of epochs pass (S) during training. To help the generalization capability of our network, we used dropout.

Table 1. Parameters used for fitting the Extra Trees model. Best model is shown in bold

Number of estimators	Minimum number of samples at leaf	Mean R^2 test score
1000	20	0.4807
500	20	0.4810
2500	20	0.4813
3000	10	0.4813
3100	**10**	**0.4916**
3125	10	0.4810
3250	10	0.4813
3500	10	0.4804

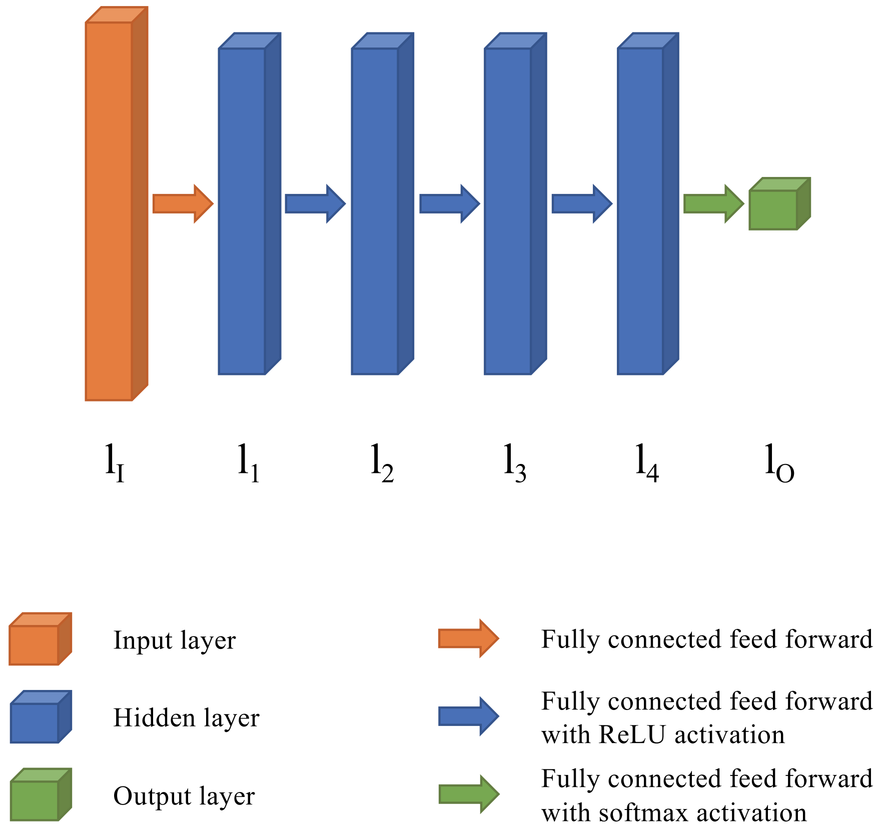


Fig. 4. Simplified structure of our artificial neural network.

We ran random hyperparameter sweeps using the Weights and Biases method (*Biewald et al.*, 2020) finding the optimal hyperparameters for the ANN. We show the individual tuned parameters and the swept ranges in *Table 2*. We trained our network with each parameter-set for 200 epochs using the AdamW optimizer (*Loshchilov* and *Hutter,* 2017), and used the cross entropy loss for training and monitoring the validation performance of the model.

The technical details of **Method 3** are not given here in the interest of guarding intellectual property rights.

Table 2. Parameter tuning of the artificial neural network. l_i denotes the number of nodes in the ith layer

Tuned hyperparameter	**Sweep range**		**Optimal value**
	min	**max**	
Batch size	16	2048	256
Learning rate	0.000001	0.01	0.0001
γ	1.5	20	2
S	10	30	15
Dropout	10%	70%	30.58%
l_1	32	512	147
l_2	16	256	151
l_3	8	256	61
l_4	4	128	5

3. Results

We trained the models for all three methods on a server computer with 2 x Nvidia RTX 2080 Super GPUs and an Intel(R) Core (TM) i7-9700K CPU running Ubuntu 22.04. The dataset preparation steps and the training scripts were developed in python using scikit-learn (*Pedregosa et al.,* 2011) and PyTorch (*Paszke et al.*, 2019).

As the aim of the models was to correctly classify the critical front type transition using binary classification, we evaluated and compared the results using confusion matrices. The no front to unstable cold front transitions are deemed critical, since they cause significant increase of accident numbers. Hence, recall is the most important metric that we want to tune the classifiers for, as this metric indicates the ratio of false negatives (i.e., cases where a critical front transition was observed, but the model missed it and the output showed no critical transition) and all positive cases in the test set. The second most prioritized metric was precision, as this metric shows the ratio of false positives (i.e., the number of cases where no critical front transition was observed, but the model output showed a critical case) and all positive predictions. The results of our training are shown in *Table 3*.

Table 3. Classification results for the trained models. Best results shown in bold

	recall	**precision**	**F1-score**	**training time (seconds)**
Method 1	68.750%	40.367%	50.867%	**0.1697**
Method 2	0.000%	*83.000%*	0.000%	166.7136
Method 3	**85.938%**	**45.833%**	**59.782%**	0.2741

Based on the recall and precision values we clearly identified, that the best candidate model for classifying critical front type transitions based on locally measured meteorological data is Method 3.

This result is also underpinned by the confusion matrices for each method shown in *Fig. 5*.

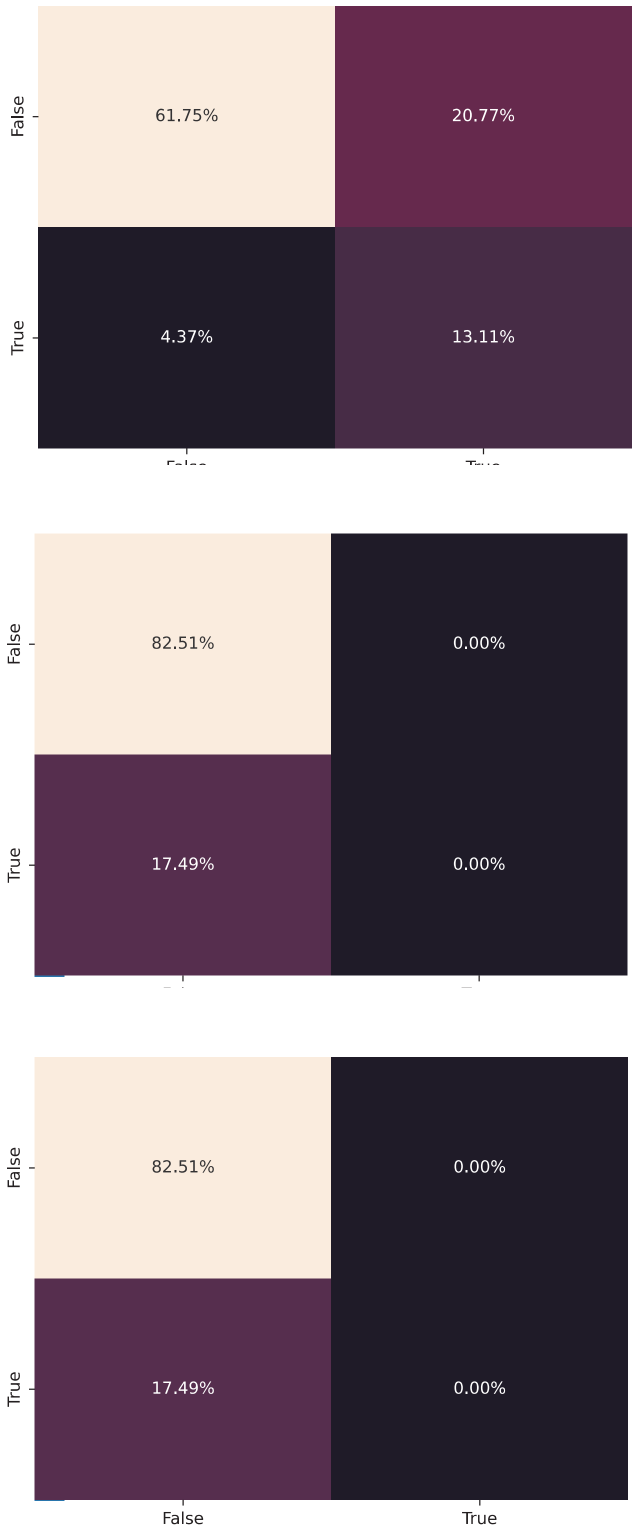


Fig. 5. Confusion matrix of Method 1 (5a), Method 2 (5b), and Method 3 (5c). True label denotes critical front transition, while False label denotes no critical front transition. The horizontal and vertical axes show ground truth values and predicted values, respectively.

4. Discussion

The high precision value observed for Method 2 (83%, shown in italic in *Table 3*) was presumably the result of the unbalanced target distribution of the test set. After further analysis of the predictions given by Method 2, it is obvious that such a high result was caused by the incapability of this method to find and learn the patterns within the training data. We also hypothesize that training that model on a larger dataset would increase its prediction ability.

Moreover, having access to a larger body of input data usually results in the training of any ML-based algorithm less prone to overfitting, i.e., the more diverse the input dataset, the less likely for the model to fit its predictions precisely to the training data. We conjecture, that the lack of ample training data caused all three models to underperform to a varying extent on the test set.

However, given that the most critical front transformation (no front to unstable cold front transition) was labeled as the positive case in the training data, our models were tuned for recall, that is, the main goal was to exhibit the highest possible recall values. An outstanding recall value was achieved by Method 1 and a satisfactory result was observed for Method 3 (see *Table 3*).

4.1. Future work

A key future development goal of our method – as mentioned several times through the previous sections – is to file for a patent and to protect the novelty of our technique.

We would like to test the possible performance gains our methods can exhibit given the availability of a larger amount of training data, as we argue that such an improvement would enable our models to become less prone to overfitting.

Another important opportunity for optimization could arise from more precise data preparation; in the current solution, feature selection for the models was performed heuristically. After that, feature usage was automatically determined by the training algorithms and the models themselves. We hypothesize that the models, more precisely the training processes, would substantially benefit from expert contributions.

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