Automatic Detection and Classification of Atmospherical Fronts

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Abstract: This paper presents an application that uses Convolutional Neural Networks (CNN) for the automatic detection and classification of atmospherical fronts in synoptic maps, which are a graphical representation of weather conditions over a specific geographic area at a given point in time. These fronts are significant indicators of meteorological characteristics and are essential for weather forecasting. The proposed method takes in a region extracted from a synoptic map to detect and classify fronts as cold, warm, or mixed, setting our study apart from existing literature. Furthermore, unlike previous research that typically utilizes atmospheric data grids, our study employs synoptic maps as input data. Additionally, our model produces a single output, accurately representing the front type with a 78% accuracy rate. The CNN model was trained on data collected from various meteorological stations worldwide between 2013 and 2022. The proposed tool can provide valuable information to weather forecasters and improve their accuracy.

1 INTRODUCTION

The atmospheric front (or air front) represents the transition between two air masses different in density or temperature. Their contact can cause radical weather changes, such as precipitation, temperature, or pressure variations. The difference in temperature between the two air groups that an atmospheric front separates determines what kind of front it is. Cold fronts, warm fronts, and occluded fronts are the three major types of atmospheric fronts. Apart from these types, there exists an additional category, stationary fronts, which have similar characteristics to occluded fronts, having in common the mix of warm and cold air masses. For the purpose of this study, we will consider both occluded and stationary fronts as mixed air fronts. The type of the front is determined by the dominating type of air mass: cold or warm. When a cold air mass approaches a warm air mass, the warm air mass is forced to ascend quickly, creating a cold front. Warm air rises, cools, condenses, and forms clouds and precipitation as a consequence of condensation. When a warm air mass approaches a cold air mass, the warm air gently rises over the denser, colder air. This is known as a warm front. As a consequence, a wide band of clouds and light precipitation are formed. When a chilly front passes by, it becomes obscured.

In synoptic-type weather maps (Bergeron, 1980), the two air masses are delimited by continuous lines, and the type of air front is determined by different geometric shapes: semicircles for warm fronts, triangles for cold fronts, and alternating triangles and semicircles for mixed fronts.

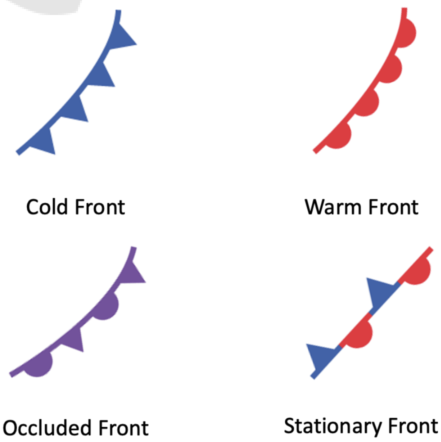

Figure 1: Types of Fronts.

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Accurate detection of atmospheric fronts holds significant importance for meteorologists and weather forecasters as it enables precise weather predictions and timely warnings. By monitoring these fronts, forecasters can anticipate weather patterns and effectively communicate potential hazards like thunderstorms, blizzards, or floods to the public. In our study, the primary research question revolves around the possibility of classifying atmospheric fronts within a smaller area (less than 350,000 sq km) using a CNN with an accuracy exceeding 60%.

This paper aims to use Convolutional Neuronal Networks on synoptic maps collected from meteorological stations to determine in an automatic manner the existence and category of fronts over the territory of a country in a specific moment. Automatic front detection is a subject addressed very little in the past years (Niebler et al., 2022) (Matsuoka et al., 2019), and only for broader territories like Europe and America.

In this paper we propose an intelligent algorithm for solving the problem of determining and classifying atmospherical fronts, using Convolutional Neural Networks. The study aims to provide an intuitive, easy-to-use, and user-friendly tool for specialists in the meteorological field that will consist aid in forecasting different weather characteristics on smaller regions, such as the territory of a country. To our knowledge, there have been no studies of the automatic classification of fronts using synoptic maps as input, therefore the model proposed in this paper aims to serve as a starting point for further research on front detection and classification in synoptic maps.

The present work is structured in five chapters as follows. The first chapter is an introduction to the problem of air front detection and its meteorological importance. Next, the following chapter presents the current state of the art in this domain, illustrating a short comparison between the existing papers and our approach. In the third chapter, we outline our comprehensive approach, including a detailed account of our methodology, the dataset collected, the pre-processing steps undertaken, the network architecture of our Convolutional Neural Network (CNN), the training process, as well as an explanation of the metrics used to evaluate the performance of our model. Moving on to the fourth chapter, we present the results of our experiments, highlighting both the strengths and weaknesses of our model. Finally, we provide a summary of our findings, outline the limitations of our model, and discuss potential ideas for further improvements.

2 LITERATURE REVIEW

The detection and classification of air fronts are usually addressed manually, but the demand for an automatic approach increased along with the dataset volume. The detection and classification of weather fronts using deep learning models is a scarcely explored field, having only a few published papers in recent years.

We are presenting two related works that utilize deep neural networks to detect and classify weather fronts. The first work 'S. Niebler et al.: Automatic detection and classification of fronts, 2022' (Niebler et al., 2022) focuses on detecting and classifying five types of fronts (warm front, cold front, occlusion, stationary front or background) over a large area using multi-level ERA5 reanalysis data, atmospherical data grids. The second work is (Matsuoka et al., 2019) 'Daisuke Matsuoka et al.: Automatic detection of stationary fronts around Japan using a deep convolutional neural network, 2019' that detects only stationary fronts in a smaller area around Japan using GPV-MSM mesoscale numerical prediction data.

In paper (Niebler et al., 2022) the authors introduced a deep neural network (U-Net) to detect and classify five types of fronts using atmospheric data grids provided by ERA5, ECMWF. The input data is represented as a two-dimensional matrix, where each cell corresponds to a specific location and time, containing weather parameters. The method used is a CNN that automatically learns atmospheric features that correspond to the existence of a weather front. For each spatial grid point, the algorithm predicts a probability distribution, the likelihood of the point belonging to one of the five classes. The validation is done through the critical success index (CSI), probability of object detection (POD), and success rate (SR). The model obtains prediction scores with a critical success index higher than 66.9% and an object detection rate of more than 77.3%. Frontal climatologies of the network are highly correlated (greater than 77.2%) to climatologies created from weather service data.

Moreover, Daisuke Matsuoka proposed a U-Net convolutional neural network that detects only stationary fronts around Japan (Matsuoka et al., 2019). The input data are weather data with multiple channels, and the output front data is a polyline that is compared with the polylines extracted from label data to optimize the model. The detection performance is evaluated by calculating the similarity between the prediction result and the ground truth based on the Tanimoto coefficient. The paper does not specify an exact estimate of the accuracy, but it provides a visual comparison of the ground truth and the detected fronts. The model succeeded in extracting the approximate shape of seasonal rain fronts, such as the Baiu front and autumnal rain front, but its performance decreased upon the approach of a typhoon.

In comparison with these papers, our study focuses on an arbitrary area, with an approximate size of an average country. Thus, the output of our algorithm contains a single result, one of the four classes. Another important distinction is the type of input our algorithm uses, the synoptic maps, in comparison to atmospherical data grids, which is an entirely different meteorological map representations. As a final distinction, our model is able to classify all 3 types of fronts on a particular area, not only discovering the existence of a particular one in a certain territory.

3 METHODOLOGY

The research plan chosen for this project requires a methodology that adopts both theoretical analysis and practical design, achieved through implementation and experimentation with different CNN models and datasets.

3.1 Dataset

The input data of the problem is represented by sets of "synoptic map" type images, collected from different weather stations, in which different meteorological characteristics are represented: air pressure, temperature and humidity, baric tendency, wind direction and speed. Thus, the model aims to detect the air fronts over a small chosen territory from the initial synoptic map. The format of the map is presented in 2. The study uses synoptic map datasets, downloaded

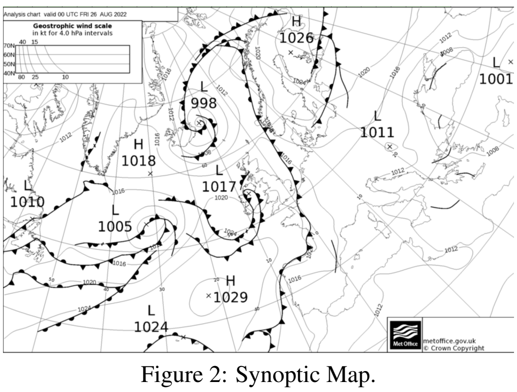

Figure 2: Synoptic Map.

from Wetterzentrale (wet,), a German weather service that provides synoptic maps daily. The data was manually collected by the authors, obtaining roughly 650 synoptic maps from different years and seasons between 2013-2022.

3.2 Input Preprocessing

The approach in this paper involves a few steps of preprocessing of the input data. The initial images received from the weather stations cover the Europe continent, containing multiple or even all types of fronts, making the result of the classification meaningless. To obtain input data that can be classified under a predominant class, the synoptic maps were divided into 9 equally sized tiles. This method lowers the chance of an image containing multiple fronts, as it covers a smaller area. The tiles were manually labelled into one of the 4 categories (no front, cold front, warm front or mixed front) by the most predominant one, if there were multiple present in the picture. To generate more data, we augmented the data by rotating the tiles with 90, 180 respectively 270 degrees, thus generating another 3 front lines with different directions. Using this method, we gathered roughly 160 pictures per class from which 25% were used for validation purposes.

To avoid overfitting to one class, we have used equally sized datasets from each category for the training and validation data. In order to increase the performance of our CNN in real life situations we have used both simple, easily identifiable fronts and more complex pictures illustrating multiple types of fronts, having a predominant one. This makes our datasets more realistic and relevant.

3.3 Network Architecture

The algorithm used is based on the classical model for image recognition through supervised learning, making use of Convolution Neural Networks with multiple convolution, pooling and dropout layers.

Convolutional Neural Networks (CNNs) are a type of neural network that is commonly used in image and video recognition tasks. CNNs are specifically designed to effectively handle spatial input data, such as images, by leveraging a series of convolutional layers (O'Shea and Nash, 2015). A CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The input to a CNN is a tensor, typically representing an image, which is passed through a series of convolutional layers. Each convolutional layer consists of a set of filters that are convolved with the input tensor to produce a set of output features.

The filters used in the convolutional layers are learned during the training process, allowing the network to learn features that are specific to the input data. These learned features are then used to classify the input data.

Pooling layers are used to downsample the output features from the convolutional layers, reducing the spatial dimensions of the data while preserving the most important information. This helps to reduce the number of parameters in the network, making it more efficient to train.

Finally, the output from the last pooling layer is passed through a series of fully connected layers, which perform classification on the features extracted by the convolutional and pooling layers.

The CNN architecture used in our paper is depicted in 3.

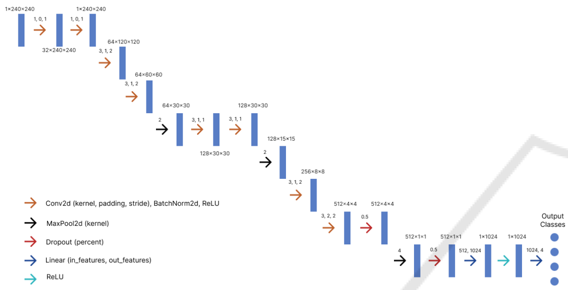

Figure 3: CNN model.

Our CNN model starts with images of a minimum size of 240x240, as they are all adjusted to this resolution before entering the first layer. The model is organized in multiple 2D convolution layers, taking into consideration the format of the input image (black and white) which is represented with only one slice, average pooling, and dropout layers, which help prevent overfitting. The last step of the neural network is the flattening phase, outputting the probability of the input belonging to each of the 4 classes. For the first layer, the number of input channels is 1 because the algorithm uses black-and-white images. After the 2D convolution is applied, the layer performs, in addition, a batch normalization and a rectified linear unit function (ReLU). All of the convolutional and pooling layers form the sequential layer, which is followed by the flattening phase.

3.4 Training Process

The phases of the Training and Validation process are presented in Figure 4.

Our experiments start with loading the data, being split into train and validation data. These two are shuffled into batches of 32 images, in order to maximize the probability of having each type of front in all batches to acquire knowledge about all fronts after processing each batch.

The training phase starts with no accuracy, slightly increasing over the epochs. In each epoch, the algorithm trains the model and iterates over batches of images loaded from the training dataset. The classes are predicted using images from the current batch and the output is compared to the actual labels. The loss function used is cross entropy and it backpropagates the loss into the network. This allows the parameters to be adjusted according to the computed gradients.

After the iteration, the learning rate is adjusted, decreasing with the current epoch. The train loss and accuracy are measured using the predictions and the actual labels for all images from each batch. The validation phase evaluates the model on the corresponding dataset and saves the model if greater accuracy is obtained.

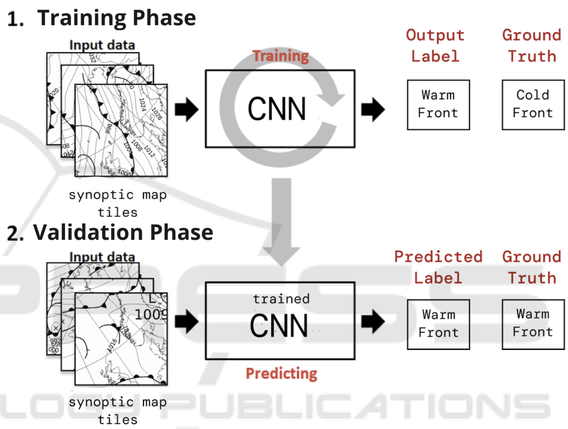

Figure 4: Conceptual Diagram of Training and Validation Process.

3.5 Metrics and Performance Assessment

In order to evaluate our method we are measuring the number of correctly classified fronts, computing the overall and by class accuracy. We also compute a confusion matrix to better visualize the performance of our CNN model. We display this matrix as a heatmap and we plot the evolution with each epoch of the overall and by class accuracy.

A *Confusion Matrix* for multiple classes is a matrix that summarizes the performance of a machine learning model by comparing the predicted class labels with the actual class labels. It is a valuable tool for evaluating the performance of a model and can be used to calculate various metrics to assess its effectiveness.

In our case, the confusion matrix is a square grid having the number of rows equal to the number of classes. Each row in the confusion matrix represents the instances in a predicted class, while each column represents the instances in an actual class. The value in each cell (i,j) of the matrix represents the percentage of instances that were classified as i but actually belonged to j. Therefore, our aim is to have the largest percentages on the main diagonal, which represents the percentage of correctly classified instances.

Accuracy is a measure of how well a predictive model is able to correctly predict the outcome or class label of a given input. Formally, accuracy is defined as the ratio of the number of correctly predicted instances to the total number of instances in the dataset. In multi-class classification problems, where there are more than two possible classes, the number of instances that were correctly classified as each class needs to be counted separately. The accuracy for multi-class classification is then calculated as:

$$Accuracy = \frac{correct\ classifications}{all\ classifications} \tag{1}$$

Therefore, in order to monitor the accuracy of our model after learning in each epoch, we are plotting the evolution of our accuracy during training.

This paper tests the hypothesis that atmospheric fronts covering a small area (less than 350000 sq km) can be classified by a CNN with an accuracy of over 60%. For each epoch, we measure the training loss and train and validation accuracy. If the validation accuracy is better than the best accuracy measured so far we save the model and upgrade the best one. We train the model over 100 epochs, saving intermediary best models.

In comparison with other articles, because the aim of our experiment was classification and not detection of the fronts as in (Niebler et al., 2022), we were able to measure the performance of our algorithm numerically, as described above, through the number of correctly classified pictures, making use of all the classic performance assessment methods used in the ML field.

4 RESULTS AND DISCUSSIONS

This study involved conducting experiments using two models with different architectures, which will be detailed in the following sections. These sections will compare the training datasets, architectures, and results obtained from the experiments. It is worth mentioning that the second approach demonstrates a notable improvement resulting from modifications made to the model structure and enhancements in the data quality utilized in our study.

4.1 Initial Version

To better understand the problem and the input data we started experimenting with a model similar to the one developed in paper (Niebler et al., 2022), having a simplified U-Net architecture in order to suit our smaller images better. We observed that the model shows lower performance on our data. The architecture can be observed in Figure 5 and the results of the validation data can be observed in Figure 6. The dataset used for the first experiment contains ≈ 300 images.

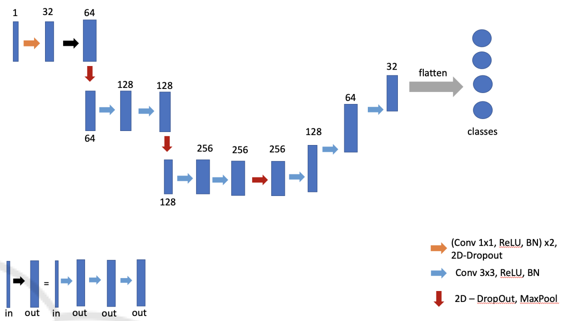

Figure 5: CNN Model Version 1.

By analyzing the results obtained we noticed that the model can easily detect the presence of a front but classifying the type of front has a lower performance.

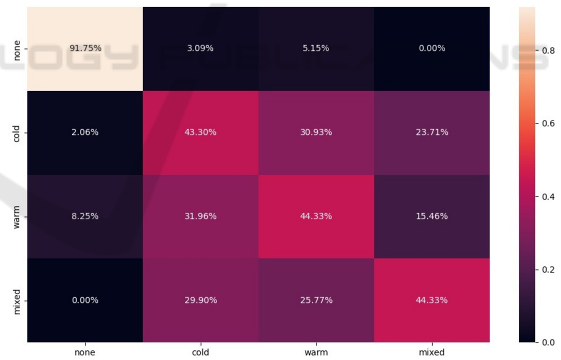

Figure 6: Confusion matrix Version 1.

4.2 Final Version

The first improvement brought to the model focuses on enhancing the training and validation datasets by adding more input data and improving its quality, both by using higher resolution images and filtering out images that were too hard to classify usually because more than one front could be identified. The architecture of the model is also improved, with a new approach that can be visualized in Figure 3.

The best model we obtained during the training phase had an accuracy of 78% and was saved after the

20th epoch. We provide the accuracy overall and the accuracy per class evolution in Figure 7 and Figure 8.

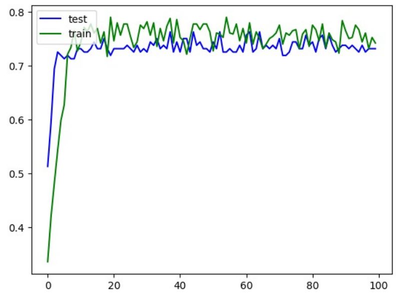

Figure 7: Train and Validation Accuracy.

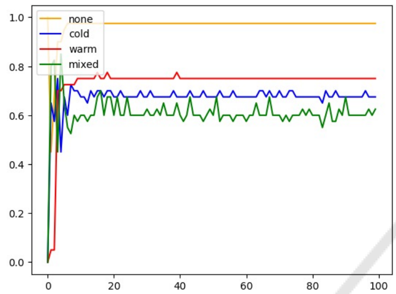

Figure 8: Accuracy Per Class Evolution.

It is noticeable that in the overall accuracy plot, our model learns the most in the first 20 epochs of the training, converging towards an accuracy of 78% in the following epochs. The oscillation of the accuracy in the first epochs is present due to the encountering of a new class in the processed batch of the current epoch. In the accuracy per class plot, it is evident that our model demonstrates proficient performance in detecting the presence of a front and a similar accuracy in detecting cold, warm, and mixed fronts.

A more refined overview of the performance is provided by the confusion matrix described in Figure 9, obtained by plotting it as a heatmap.

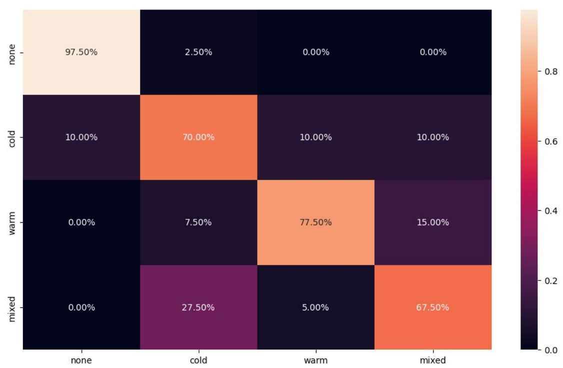

Figure 9: Confusion matrix.

It can be observed that the model's biggest flaw is its tendency to misidentify cold fronts as mixed fronts, with a 27.5% error rate. This issue arises because of the quality of our data, some of the synoptic map tiles contain both warm and cold fronts (with cold fronts being the predominant ones) and our model may mistake a tile with a cold and a warm front with a mixed one. The difference between the two cases consists of the fact that the two polylines of the fronts may overlap and create the illusion of a mixed front, as can be observed in Figure 10.

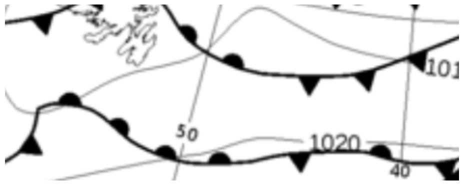

Figure 10: Cold and Warm Fronts Alternatively.

5 CONCLUSIONS AND FURTHER WORK

The main conclusion that can be drawn is that Automatic Front Detection can be a very efficient solution for the issues we currently face in weather prediction. Our study demonstrates that a supervised learning model, even with a relatively small training dataset, can accurately classify the types of fronts present on a small area from a synoptic map. One of the most important strengths of our approach is that our experiment paves the path for further research and for the discovery of new approaches in the domain, which is currently very little represented in the research world. Considering that, to our knowledge, this research is one of the first to approach front classification on small areas, we have encountered a few shortcomings in our experiments. One of the most relevant weaknesses to our approach is the training dataset, which is very hard to obtain and label because they are not publicly available in larger sets. In addition to this, the synoptic maps might not be consistent in the future, depending on how meteorologists decide to represent the fronts.

There is definitely room for improvement in the model developed, as it is one of the first to approach this issue. Two possible directions that could increase the performance are larger, more qualitative training datasets and more efficient processors that could support more epochs of training.

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REFERENCES

https://www.wetterzentrale.de. Online; accessed 15 June, 2023.

Bergeron, T. (1980). Synoptic meteorology: an historical review. *Pure and Applied geophysics*, 119(3):443–473.

Matsuoka, D., Sugimoto, S., Nakagawa, Y., Kawahara, S., Araki, F., Onoue, Y., Iiyama, M., and Koyamada, K. (2019). Automatic detection of stationary fronts around japan using a deep convolutional neural network. *SOLA*, 15:154–159.

Niebler, S., Miltenberger, A., Schmidt, B., and Spichtinger, P. (2022). Automated detection and classification of synoptic-scale fronts from atmospheric data grids. *Weather and Climate Dynamics*, 3(1):113–137.

O'Shea, K. and Nash, R. (2015). An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*.