MAP 2192 - Mathematics for Data Science: Final Project Report

# Utilizing Relative Velocity Radar Images and AlexNet for Distinguishing Tornadoes from Thunderstorms

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## Abstract

Tornadoes present a significant challenge due to their unpredictability and potential for destruction. Traditional detection methods, which often rely on broad-area weather forecasts, lack the precision and timeliness required for effective early warnings, a deficiency particularly acute during nocturnal hours.

At the heart of TornadoTracker's methodology is the integration of AlexNet, a convolutional neural network, with relative velocity radar images. This report details the process of assembling a specialized dataset composed of radar images depicting tornadoes and thunderstorms. The AlexNet model is trained on this dataset, focusing on differentiating the distinct signatures of tornadoes from those of general thunderstorm patterns. The training process and the selection rationale for AlexNet are thoroughly examined.

The results of this study underscore TornadoTracker's proficiency in accurately identifying tornado formations, with the model achieving a high accuracy rate. The analysis of the model's performance, including accuracy and loss metrics, is presented. Feature maps generated by AlexNet offer valuable insights into the model's pattern recognition capabilities within complex meteorological data.

The study concludes with a discussion on the broader implications of TornadoTracker for meteorological practices and public safety. It highlights the transformative potential of machine learning in enhancing weather forecasting, especially in regions with limited meteorological infrastructure. Additionally, the discussion touches on the current model's limitations and the potential for future advancements, such as incorporating more diverse data sources and exploring advanced neural network architectures, to further refine and enhance tornado prediction capabilities.


## 1 Introduction

The inception of the TornadoTracker project was born out of a personal encounter with the inadequacies of current tornado warning systems. This realization came during an event where multiple tornado warnings were issued, yet there was a striking lack of specific information regarding the tornado's location and timing. The general nature of these alerts, coupled with the absence of cable news or easily accessible online resources, highlighted a critical gap in tornado detection and reporting: the absence of personalized, location-specific warnings.

This project's relevance is underscored by the behavioral patterns observed during tornado occurrences. While people are generally more vigilant and actively seek information during the day, the situation drastically changes at night. Nighttime poses a greater risk as individuals, often asleep, might disregard general warnings due to their frequent, non-specific nature. This scenario emphasizes the need for a more precise and personalized alert system, capable of providing timely and accurate information about imminent tornado threats.

The TornadoTracker project, therefore, centers around leveraging AlexNet, a convolutional neural network, to discern between radar images of tornadoes and thunderstorms. The choice of AlexNet was driven by its proven capabilities in image classification tasks, particularly in differentiating subtle features within complex visual data. The primary aim was to test the model's effectiveness in analyzing relative velocity radar images, a critical component in modern meteorological practices, to identify tornado formations accurately.

A significant challenge encountered in this endeavor was the scarcity of suitable datasets. The lack of readily available, categorized radar images necessitated a manual approach to data collection. Utilizing Radarscope and a historical tornado track tool, extensive efforts were made to compile a dataset that accurately represents the visual characteristics of tornadoes in relative velocity radar images. This painstaking process involved correlating historical tornado tracks with corresponding radar imagery to create a robust dataset for model training.

The potential implications of TornadoTracker are profound. By enhancing the accuracy and specificity of tornado warnings, it promises to significantly improve public safety, especially during critical night hours. This study not only explores the technical feasibility of using machine learning for advanced meteorological forecasting but also opens avenues for future innovations in weather prediction and disaster management.

## 2 Materials & Methods

In the TornadoTracker project, our methodology was centered around the collection, preprocessing, and analysis of a dataset comprising 50 images, with an equal distribution of tornado and thunderstorm images. These images were sourced from Google Slides presentations, where they were initially stored in PDF format. Utilizing the pdf2image library, we converted these PDFs into image files, a crucial step in preparing the data for further processing.

Once the images were extracted, we employed a series of preprocessing steps to standardize and prepare them for input into our machine learning model. This preprocessing involved resizing the images to a uniform dimension of 224x224 pixels, followed by center cropping. We then converted these images into tensor format, a necessary step for compatibility with PyTorch, our chosen machine learning library. The final step in preprocessing was normalization, where we adjusted the pixel values of the images based on predefined mean and standard deviation values. These steps were crucial for ensuring that the input data was in an optimal format for effective model training and analysis.

For the implementation of our machine learning model, we chose AlexNet, a well-known convolutional neural network architecture available through PyTorch's torchvision.models module. AlexNet was selected for its proven capability in image classification tasks. We ran our model on a CUDA-enabled device, leveraging the power of GPU acceleration to enhance the efficiency of our computations. This choice was dictated by the need for processing large volumes of image data, where GPU acceleration could significantly reduce computation time.

The training process involved feeding the preprocessed images into the AlexNet model. The output from the model was then normalized using a softmax function, which is standard practice in classification tasks as it converts the output into a probability distribution. Following this, we applied a cross-entropy function to calculate the loss, which measures the difference between the predicted outputs and the actual labels of the images. An Adam optimizer, known for its efficiency in handling large datasets and complex architectures, was employed to optimize the model parameters.

Throughout the training process, we utilized the Weights & Biases platform, commonly abbreviated as wandb. This tool was instrumental in tracking our experiment's progress, logging various metrics such as accuracy and loss. By visualizing these metrics, we could gain insights into the model's performance and make necessary adjustments to our training process.

## 3 Results

In the TornadoTracker project, the results of our machine learning model, specifically the implementation of AlexNet, were quantitatively assessed based on two primary metrics: accuracy and loss. These metrics are crucial indicators of the model's performance in classifying radar images into tornado and thunderstorm categories. The accuracy of our model reached 93.2%.

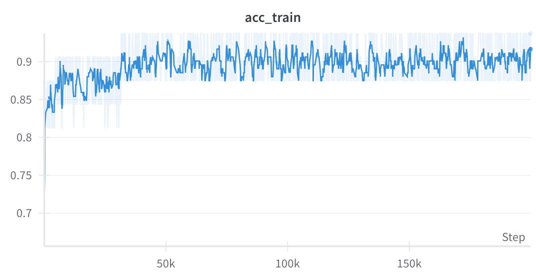


Figure 1: Training Accuracy Plot

This high accuracy rate indicates that the model was highly effective in correctly identifying and categorizing the images. In the context of our dataset, this means that the model was able to distinguish between tornado and thunderstorm images with a high degree of precision.

Alongside accuracy, the loss metric was also evaluated, with our model achieving a loss value of 0.42. In machine learning, the loss is a quantification of the difference between the predicted values by the model and the actual values. A lower loss value is generally indicative of a better model performance. In our case, a loss of 0.42 suggests that the model's predictions were relatively close to the actual labels of the images, further underscoring the effectiveness of our approach in classifying radar images.

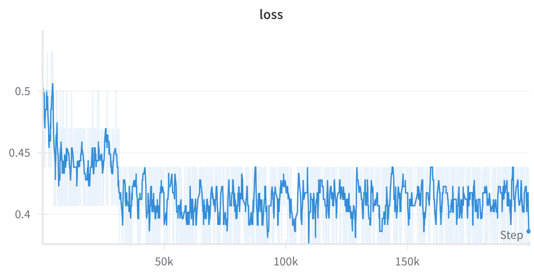


Figure 2: Training Loss Plot

In summary, the results from the TornadoTracker project demonstrate the capability of the AlexNet model to effectively classify radar images into tornado and thunderstorm categories, as evidenced by the high accuracy and low loss metrics. These results are a testament to the potential of machine learning models in advancing meteorological analysis and prediction.

## Conclusions

The TornadoTracker project, through its successful implementation of the AlexNet convolutional neural network for classifying radar images, has demonstrated significant potential in enhancing tornado detection and forecasting. The high accuracy and low loss achieved in our model underscore the feasibility and effectiveness of applying advanced machine learning techniques to meteorological data analysis.

Future studies could explore the integration of additional data sources, such as satellite imagery or ground-based sensor data, to further refine the model's predictive capabilities. The exploration of more advanced neural network architectures, like deep learning models that can process sequential data, could provide even more nuanced insights into weather patterns and storm formation.

Another promising direction for future research is the development of real-time analysis systems. Implementing our model in a real-time environment, where it can analyze live radar feeds, would be a significant step towards proactive disaster management and response. Additionally, expanding the scope of the model to include other types of severe weather events, such as hurricanes or severe thunderstorms, could broaden its applicability and impact.

In conclusion, the TornadoTracker project represents a meaningful stride forward in the application of machine learning to weather forecasting and natural disaster prediction. The potential benefits of this technology in terms of public safety, economic savings, and scientific advancement are considerable. Future research building on this foundation could lead to even more innovative solutions, further bridging the gap between technology and meteorology.