The Secrets of Satellite Imagery

Predictive Modeling for International Conflict

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Abstract

Utilizing satellite imagery has a strong potential to illuminate the development of international conflicts. With advanced technological analytics and an indiscriminate scope of data, knowing what information is informative in satellite imagery would prove a satellite-based machine learning model to be an essential tool for international relations. To address this question, this research attempts to use satellite imagery of Gaza from several dates before and after the October 7, 2023 conflict to measure the conflict's development via satellite imagery. The implications from this model demonstrate that there are several problems to be worked out if a satellite imagery model is going to be successful for feature analysis of conflict landscapes. Key insights include that future models for this work should rely on classifications, binary or otherwise, with clear and limited categories to prevent skewing results. Because of this, high number of epochs are required for changes in classification to present the long-term truth of the CNN's classification attempts.

Introduction

Today, someone can make a call to speak with someone they've never met, thousands of miles away. Today, someone can type a few words into a laptop and hear news from a country they've never seen and will likely never visit. Today, someone can log onto social media and hear about the day-to-day life of someone who doesn't even know they exist. So, to this day, why is it still so difficult to identify the onset of destructive conflict before thousands of lives are lost? Why are the circumstances and severity of international conflict unknown until well after the damage has been done?

With such advanced technology available, researchers, government agencies, and nonprofits should have better methods to recognize early signs of severe conflict. With worldwide overhead access to locations' geography, satellite imagery represents one of the most promising tools to identify features of conflict.

Combining this technology with machine learning methods presents a massive potential for identification of early-onset international conflict. Having a model that can identify geographical features that signal conflict could help the international monitor, address, and provide aid for conflicts in order to limit the conflict's severity and damage. Using satellite imagery from the 2023 Israel-Palestine conflict, this research aims to develop a machine learning model that can predict the severity in the presence of conflict based on satellite imagery.

The Conversation So Far

This research is far from the first attempt to identify early signs of international conflict. Most of the research in this context centers on early warning signs of genocide. Several of these research projects consider specific cases of genocide, including Armenian genocide, Darfur genocide, and the Jewish Holocaust. These projects entail a retrospective analysis of the early warning signs that were proven to develop into defining markers of these conflicts (Chopyak, Valentyna, and Lonchyna 2024; Cooley 1996; Huq, Aziz, and Muller 2008; Karb and Beiter 2009). Other viewpoints on this topic examine a specific warning-sign in depth, such as the elimination of intelligentsia or dehumanization and toxification (Salerian et al. 2009; Nielsen 2016).

There is also some research in a similar vein, but with a more generalized scope than the genocide discussion. These researchers attempt to make a framework for identifying conflict and the indicators that are best for doing so (Cranmer, Menninga, and Mucha 2015; Ochs, Fahim, and

Pinzon 2022). On the other side of this coin, there are also discussions about the merits of these evaluation systems and their limitations (Hegre et al. 2021).

Importantly, there are also research considerations into how the international community does and should respond to early warning signs. Some scholars examine the shortcomings of past attempts and the lessons to fix them, whereas others debate the ability to effectively respond to early warning signs at all (Department… 2023; Slim 2004).

Most closely to this vein of research is the limited quantity of studies that include statistical or computational approaches to satellite imagery analysis. These studies usually examine images to explain different trends and case studies for specific conflicts or in urban landscape analysis (Pech and Lakes 2017; Chetverikov and Kropatsch 1993; Lyons 2012). These methods usually do not include any machine learning or artificial intelligence components to automate the identification process. The closest inclusion of these technologies is a satellite image analysis of the Gaza Strip conflict using AI monitoring (Zhao et al. 2024). However, this research does not *develop* a model, but rather uses a pre-developed AI model in its analysis.

This research believes it is crucial to have an automated model that can consider satellite imagery. Relying on synchronous human analysis limits the ability to identify conflict in its early stages given the scope of areas being analyzed and the time required for such analysis. As such, this research aims to fill this gap by considering satellite imagery of the Gaza Strip to develop a deep learning model that can identify the early onset of international conflicts.

Research Design and Methods

The Data

The data for this research comes from the Planet database, which hosts years' worth of global satellite image data. This project specifically centers on the Gaza strip data from various months before and after the onset of the most recent conflict — Oct 7, 2023. The data chosen represent various scenes of the GeoTiff data that provide the highest area coverage between May 2023 and December 2023.

The files in this data are four-band TIF files: red, green, blue, and near-infrared layers. For each day represented in the dataset, there is one AnalyticMS file and one usable data mask (udm2) clip. The AnalyticMS file represents an unfiltered snapshot of the satellite image's location, whereas the udm2 has been adjusted for the presence and shadows of clouds. The inclusion of both of these files in the research aims to consider any shadow differences that are influential apart from the influence of cloud data.

The dependent variable demonstrates a measure of time since the onset of the October 7, 2023 conflict. The data includes a 0 for data taken before October 7, a 1 for data on that day, and an increase of 1 for every day after October 7, 2023. The goal of this variable representation is to understand how changes in satellite imagery can be correlated with the development of the war, thus indicating the satellite-present features that could help identify early stages of international conflict.

The data will be split into testing and training categories of 70% and 30%, respectively. The divide will be randomly made for both zero and non-zero values to ensure that there are representations of both types of data in the training set.

The Shortcomings

This data was standardized with data reshaping and PCA dimension reduction so that each file attained a shape of (4, 5000, 2000). For context, the average file in the dataset had original dimensions of (4, 6488, 3649). Time requirements for this analysis demanded that the files chosen per day were those with the lowest original resolution, which could alter the quality of results. Additionally, with access limits to the Planet data, the representation of data after the conflict was shortened compared to the intended scope.

Because of this researcher's limitations with the Planet data platform, the data gathered for this research represents a very large and inconsistent geographical area across each day represented in the dataset. Similar landscapes were targeted, but slight differences caused different lengths of TIF arrays acquired for analysis. The large scope of the general region targeted could also affect the reliability of results, though PCA analysis as described attempts to offset this.

Research Methodology

The TIF data will be analyzed with a two-layer convolutional neural network. The model will include an input layer of dimensions (4000,1500,4), followed by a (2,2) MaxPooling2D layer to enable the model to run within memory restrictions. After these initial layers, the model will contain two pairs of Conv2D and max pooling layers. The first Conv2D layer will consist of 32 filters, and the second will contain 64 filters. After this will be a global max pooling layer. The final two layers will be a dense layer of 128 nodes. The final output layer will have dimensions of 85 to span each of the output values that exist in the y-data set. The convolutional layers will have relu activations, and the final layer will have a softmax activation. The pooling layers will all have dimensions of (2, 2), and the Conv2d layers will have a kernel size of (3, 3) with strides of (2, 2).

Results & Analysis

The convolutional neural network produced moderately accurate results. Surprisingly, the test accuracy was higher than the training accuracy.[1] Considering this fact, the retrospective explanation is that the random assignment of the training data for the experiment, proportionally, had slightly less zeroes than the testing data. This suggests that the model is more apt at recognizing zeroes than non-zeroes.

This idea is corroborated by the confusion matrix, which plotted the actual versus predicted values using a scaled-down version of the data.[2] According to this plot, not only are most of the guesses zero, but the highest proportion of accurate guesses were by far the zero guesses. This suggests that the accuracy metrics might not differ significantly from random guesses of the model that entail zero and non-zero values.

Reflections on this model demonstrate how the experiment set-up could affect the appearance of model accuracy. Instead of looking for exact values, future research could consider an "accurate" prediction to be within, for example, 3 days of the actual value. So, if a model predicted the data to have been collected 64 days after the conflict started, but in reality it was 65, this model would have considered this incorrect. However, for practical reasons, this is still a close estimate that could provide useful information for applicative analysis.

Model Adjustments: Binary Classification

Based on the above analysis, this research decided to add a model with the same properties with alterations in the y-data classification. Instead of relying on exact date metrics, the y-data became a flag metric with classes of 0 and 1. The aim of this was to test whether the model was attempting to distinguish between zero and non-zero values, or if higher y-values present in the original dataset were affecting the ability of the model to identify zero values. In the y dataset.

The accuracy percentages, .56 for training and .63 for testing, do not represent any significant analytical differences compared to the original dataset, suggesting that the model was actually creating intentional differences in zero and non-zero values and was not strongly deterred by the range of non-zero values in the y dataset. However, the confusion matrix for this adjusted binary model counteracts this idea, seeming to prove that the model relies on predicting zeroes.[3] Throughout the entire binary model, only one prediction was for a non-zero value, and it was an incorrect prediction.

Model Adjustments: Validation Data

In order to further illuminate the issues described above, this research also attempted to use two models with validation data – model 4 for the multi-class classification model, and mode 3 for the binary classification model. These included the last 12.8% of the training data as included in the validation section, and allowed for two training and testing plots to view the model's metrics throughout training.

Surprisingly, the validation model for the binary model had a notable improvement in the training accuracy of the model.[1] There was also much less loss, and a significant reduction in training time, which could indicate productive effects for having a reference image that is not included in the training data itself. This small change represents a marked improvement for the model, which – although had a large reduction in test accuracy – attempted to differentiate between more inputs than just relying on zero guesses.

The training curves of this model demonstrate the inside process where such differentiations occurred.[5] The first fifth of the 200 epochs represented a decline in accuracy, which then sharply rose again and remained consistent for the rest of the model. This suggests that the major adjustments occur in the early phase of the model. The loss curve, however, is a slow and steady decline. So, as major adjustments are made at the beginning of the model, having enough time to continue analysis provides a more accurate picture.

This is more difficult to see in a binary model with only two outputs, but model 4 did not deliver on its potential to provide further insight into this question. The validation curves for model 4 in combination with the confusion matrix demonstrate that this validation model did not attempt to differentiate between zero and non-zero values.[6, 7] This demonstrates that specifically-identified features are not the best form of this analysis, but rather that the lowest number of possible classifications is best for satellite imagery.

The implications from this model demonstrate that there are several problems to be worked out if a satellite imagery model is going to be successful for feature analysis of conflict landscapes.

Conclusions

Utilizing satellite imagery has a strong potential to illuminate the development of international conflicts. With advanced technological analytics and an indiscriminate scope of data, knowing what information is informative in satellite imagery would prove a satellite-based machine learning model to be an essential tool for international relations.

However, the use of a convolutional neural network with dimension-reduced TIF data needs to be further explored before this method can be considered a fruitful attempt at machine learning classification. There are several potential improvements that could aid this process. One is to use a smaller geographical area so that differences in data values are more specific and meaningful. Additionally, having a defined and consistent geographic region could help eliminate alterations in results based on falsified differences in data based on representation.

Lastly, including a more expansive timeframe that allows for the development of post-conflict differences in satellite imagery.

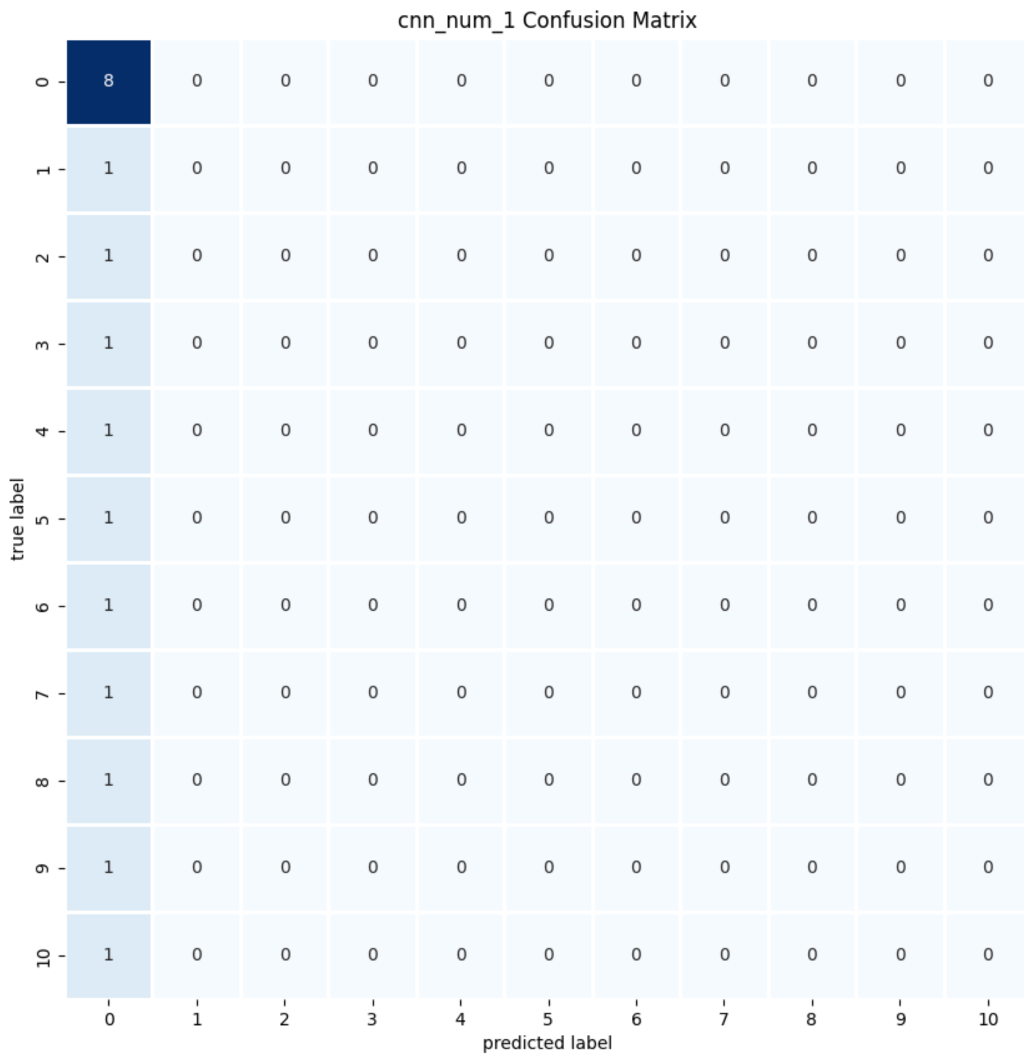
Although this research did not provide the intended conclusive results, there are still important considerations that inform the ultimate goal of this research: illuminating how satellite imagery research can be used for predictive modeling in conflict analysis. For one, predictive modeling should rely on binary analysis as much as possible. Small differences in satellite imagery could mean big differences in conclusions, and utilizing binary classification helps to eliminate the risk of false differences that skew results. Additionally, a higher number of epochs is crucial to allow the model to slowly develop a lower loss value. With binary modeling, it could take more time for this change in loss to show itself in final results, and allowing time for this to develop will help ensure that final results demonstrate the full trend of the model's training process.

APPENDIX

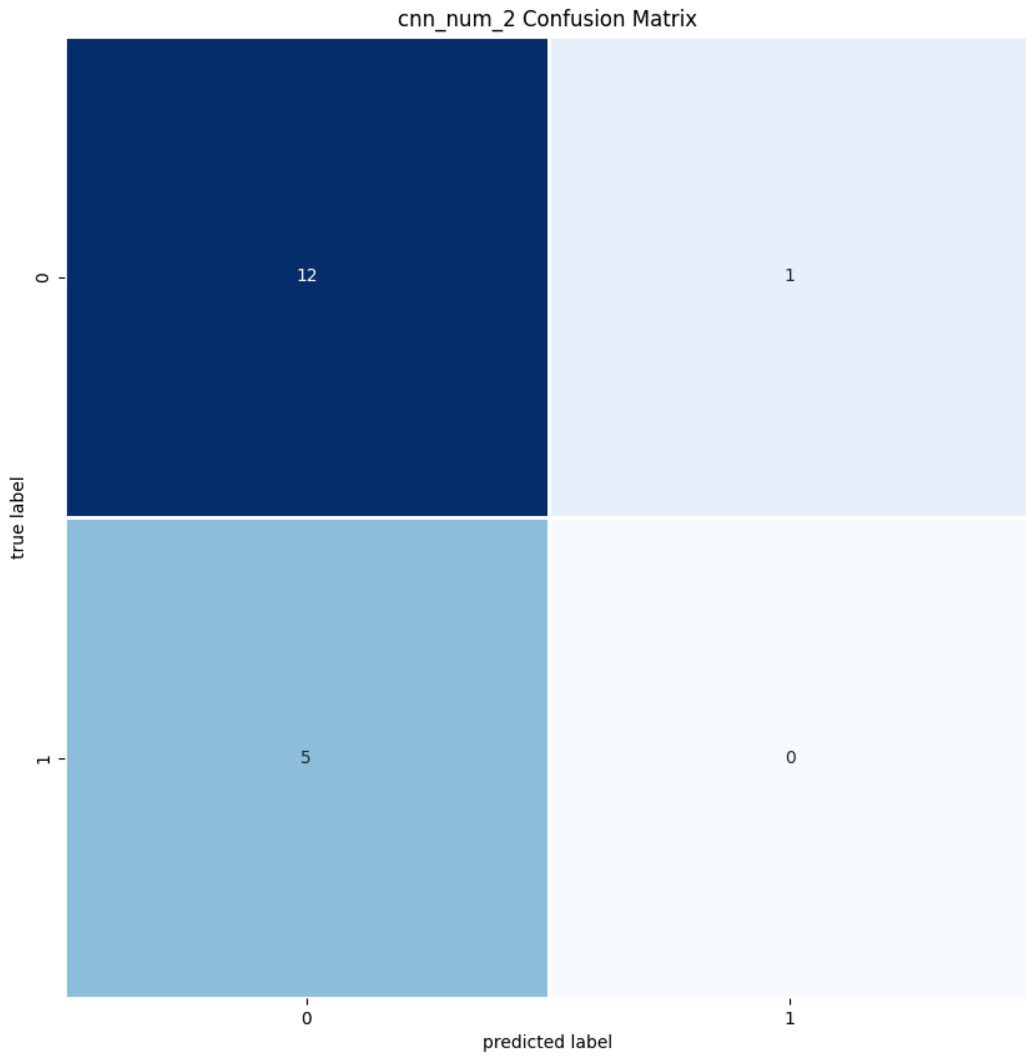
1. Model Accuracy Metrics

Model	Loss	Test_acc	Train_acc	Time (seconds)
cnn_num_1	1.822834	.611111	.564103	711.476934
cnn_num_3	.670631	.333333	.676471	27.458505

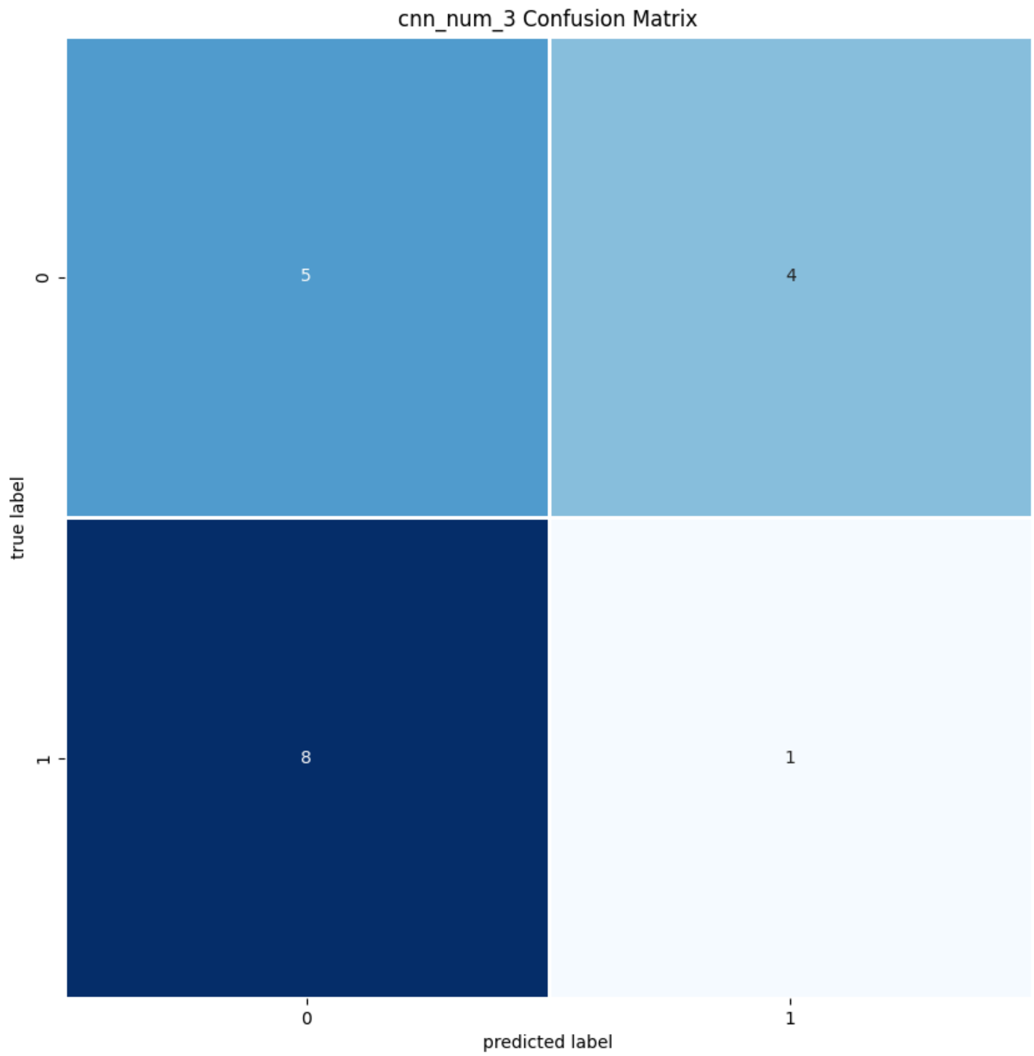
2. Confusion matrix for Model 1



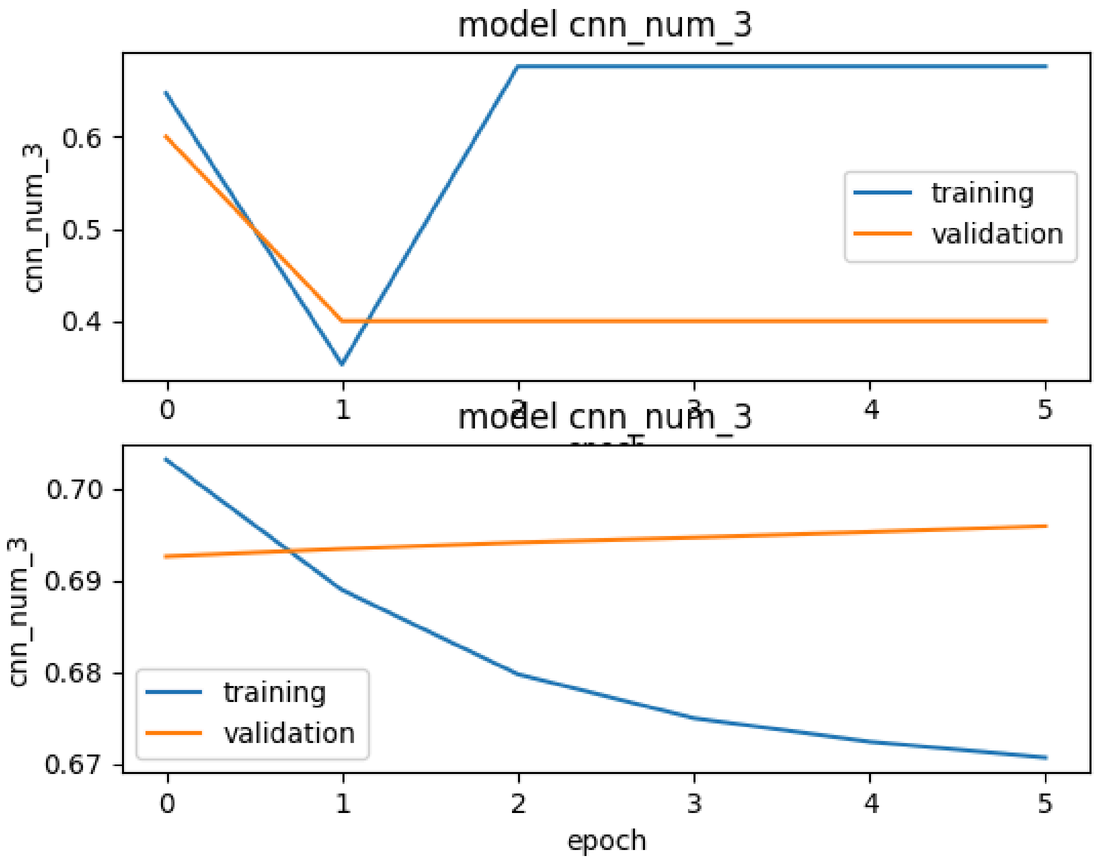
3. Confusion Matrix for Model 2



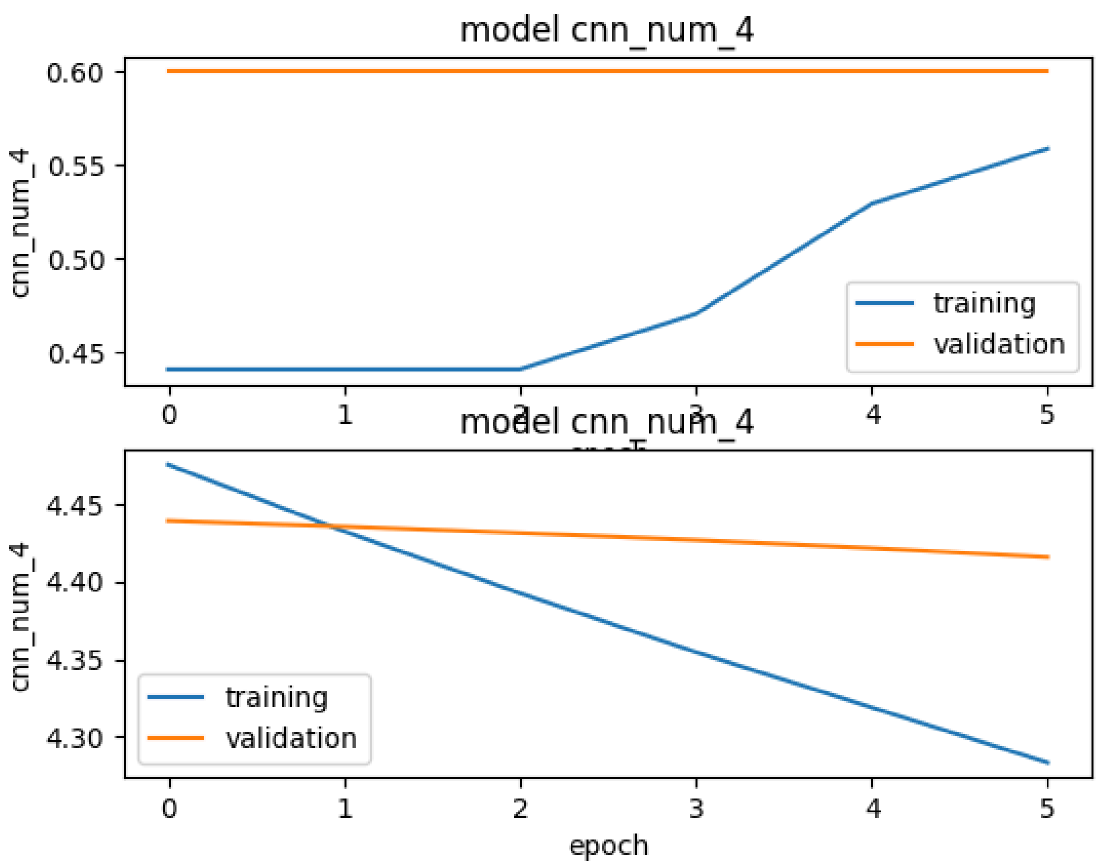
4. Confusion Matrix Model 3



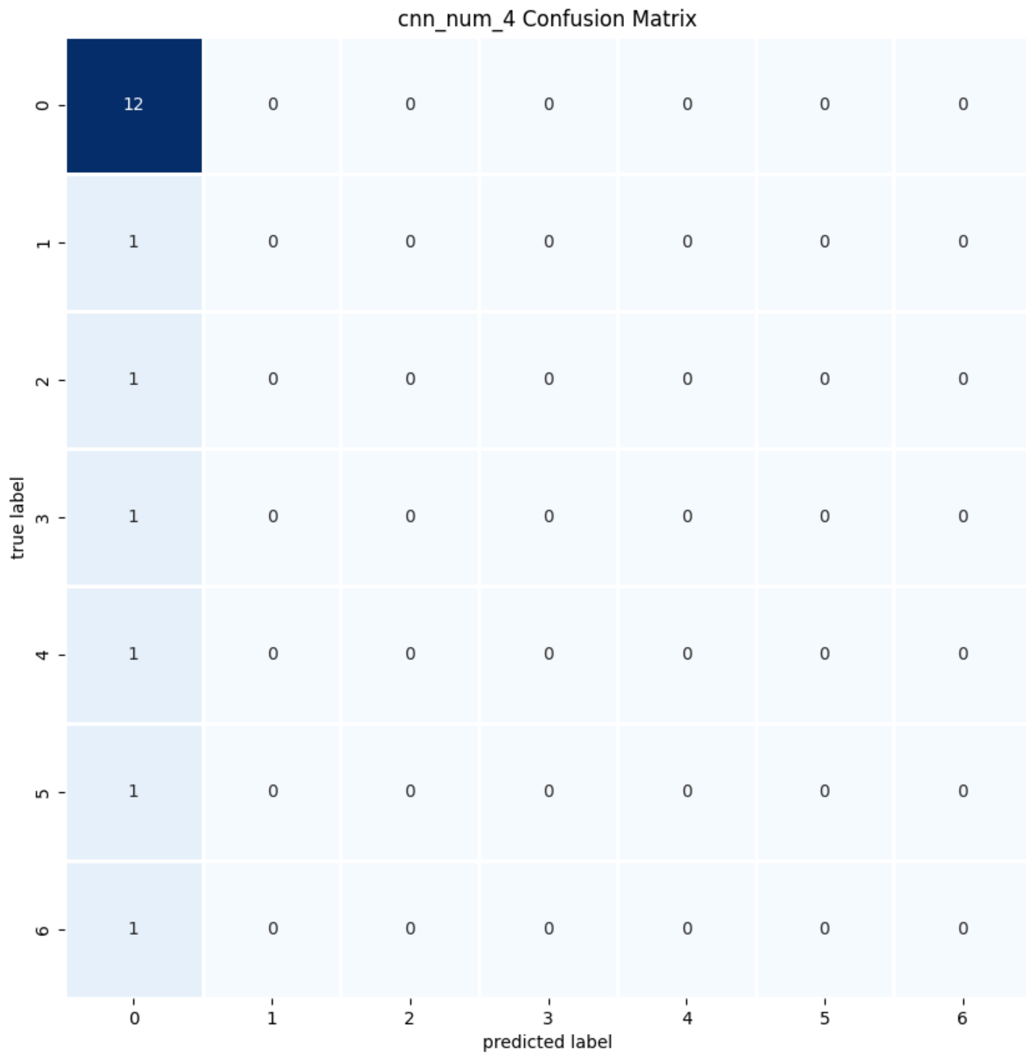
5. Training Curves Model 3 (Top: Accuracy; Bottom: Loss)



6. Training Curves for Model 4



7. Confusion Matrix Model 4



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