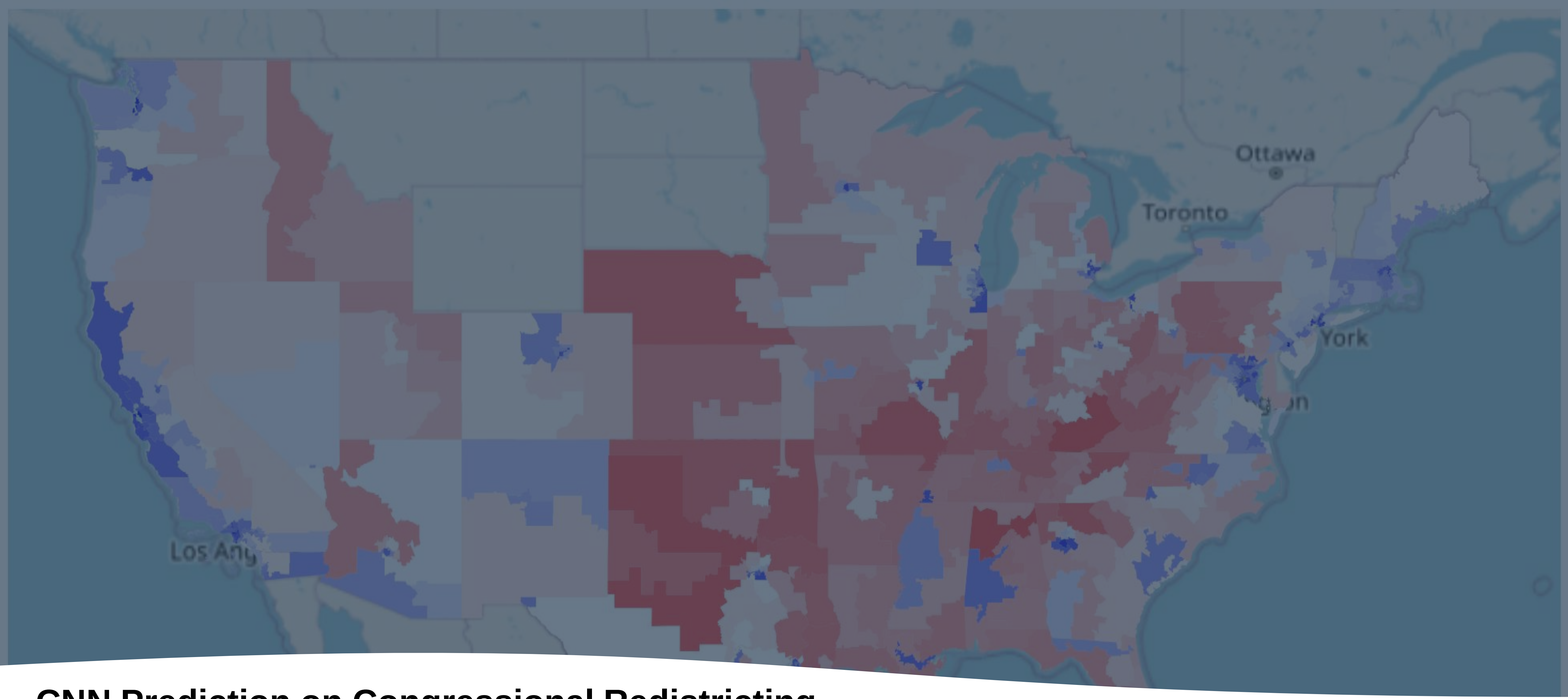

CNN Prediction on Congressional Redistricting

Evaluating the Impact of 2021 Nationwide Redistricting on 2024 US Presidential Elections

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Goal: Training CNN to Evaluate Impact of 2021 Gerrymandering on 2024 Presidential Elections

Problem Statement

Gerrymandering district boundaries is proven to **illegally and significantly impact voting outcomes**, but it is currently very difficult to **evaluate degree of gerrymandering to predict impact of redistricting on future election outcomes**

Project Scope

Predicting gerrymandering outcomes by applying a **convolutional neural network (CNN)** on redistricted congressional district maps to evaluate the presence and partisanship of gerrymandering in 2021 congressional districts

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Analytical Process

(1) Calculate academic metrics to measure historic gerrymandering
(2) Create standardized maps of redistricting instances as input for CNN to train/test on
(3) Train CNN with appropriate metrics, correcting for underfitting/overfitting as necessary
(4) Predict gerrymander outcomes of 2021 redistricting; infer outcomes on 2024 elections

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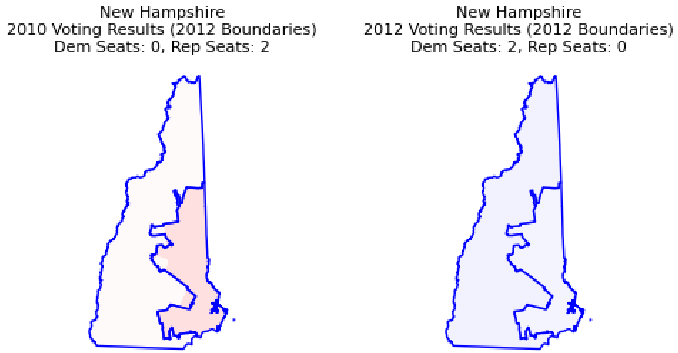
Findings

Best CNN model performance could not perform better than random – likely due to a mixture of non-ideal model architecture, inefficient input map data, small input sample size, and insufficient computational resources

Understanding Gerrymandering

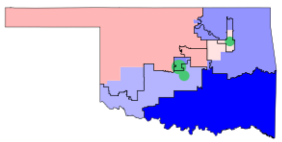
1. What is "Gerrymandering"?



- **Gerrymandering** refers to redrawing state lines (redistricting) to **favor voting outcomes** for one political party
- Gerrymandering **is illegal in the US** since the 1960s (on grounds of racial profiling), but both parties still rampantly gerrymander
- Example: **REDMAP** allowed Republicans to **win the 2012 House elections by 33 seats despite losing nationwide popular vote**
- All eligible states redistricted in 2021 – **16 states** are currently in litigation to redraw boundaries over gerrymandering

2. How can we measure Gerrymandering?

2002 Nebraska Redistricting
Republican Vote: 56%
Republican Seat: 3/0 (100%)
Efficiency Gap: +0.38

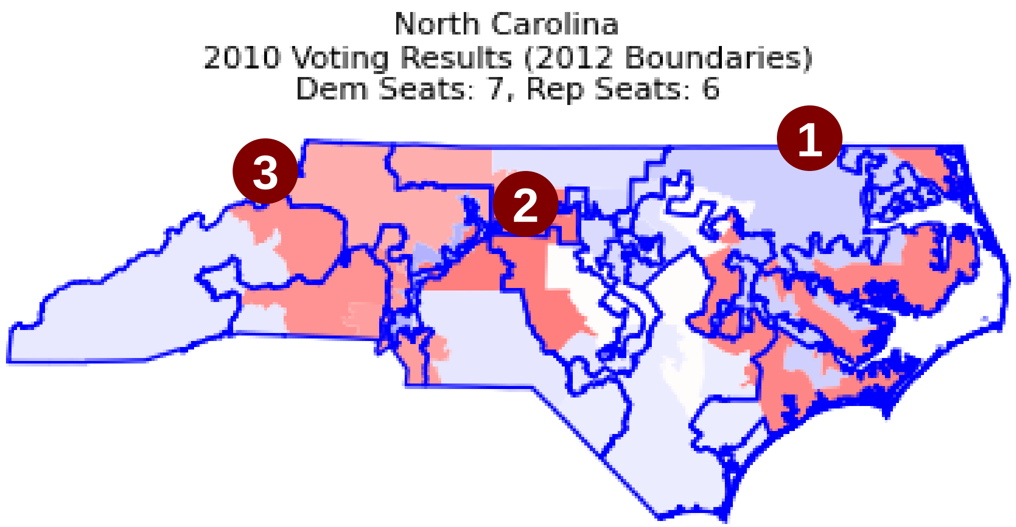


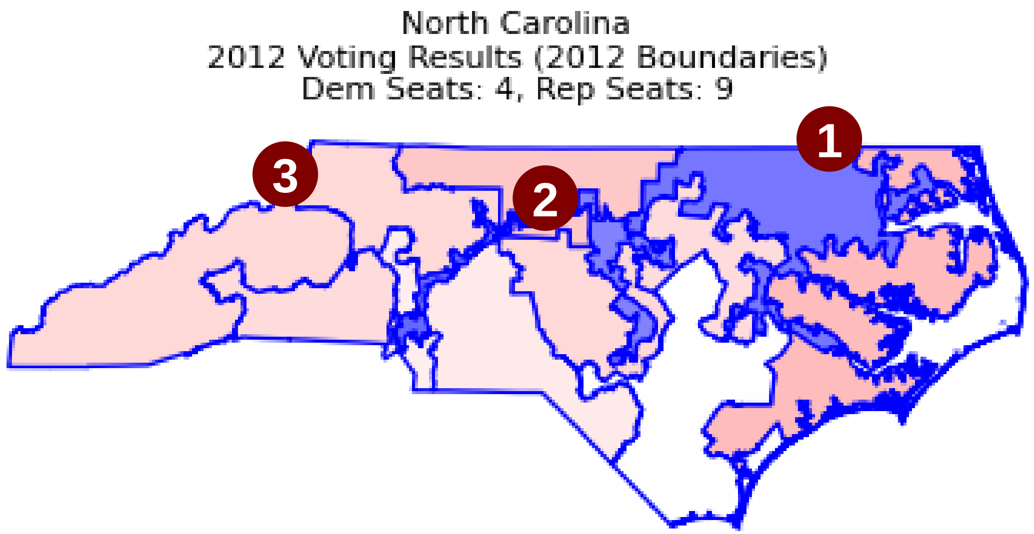
1974 Oklahoma Redistricting
Democrat Vote: 59%
Democrat Seat: 0/6 (100%)
Efficiency Gap: -0.33

- **Efficiency Gap** is a widely-used simple metric used to measure gerrymandering in a state
- Negative scores indicate Democratic gerrymandering and vice versa, magnitude of scores indicate severity
- **Efficiency Gap Swings** (post-change – pre-change score) can be used to see landscape changes over redistricting cycle

Gerrymandering district boundaries is proven to **illegally and significantly impact voting outcomes**, but it is currently very difficult to **evaluate degree of gerrymandering to predict impact of redistricting on future election outcomes**

A Classic Example: Changes in North Carolina after 2011 Redistricting (Project REDMAP)





1

Packing: 1st District (D+52)

Republicans packed majority-Democratic populations in Raleigh-Durham into 1 district to limit their impact, spreading Republicans majorities into surrounding districts.

2

Packing: 12th District (D+59)

Oddly-shaped district is stretched to pack urban centers of both Charlotte and Winston-Salem into 1 district, limiting the impact of Democratic voters

3

Cracking: 5th (R+15), 10th (R+14), 11th (R+15)

Previously heavily-conservative district is split into three to spread Republican majority, allowing them to flip District 11 and hold strong majorities in 3 districts.

Republicans flipped 3 seats to win the House while losing the majority vote[1] (48% Republican)

(1) Fairvote: Fairvote's Unique Methodology Shows That 52% Of Voters Wanted a Democratic House

Analytical Plan

Exploratory Data Analysis (EDA) → Feature/Target Engineering → Standardization → CNN Training → Under/Overfit Model Tuning → Predictions

Data Collection: Finding appropriate data for project

Efficiency Gap: primary metric for quantifying gerrymandering

Graphing Trends: understand landscape of gerrymandering over time

Partisan Lean: measuring winning margin for districts

Creating Maps: GeoPandas mapping for spatial data

Sense Check: ensure data matches reality

Standardization: creating images of standard size for CNN (400x400)

Mass Production: creating images for all 342 instances of redistricting

Image Augmentation: increasing training dataset size through augmenting data

Class Imbalance: creating images for all 342 instances of redistricting

Baseline Model: setting benchmark to improve on

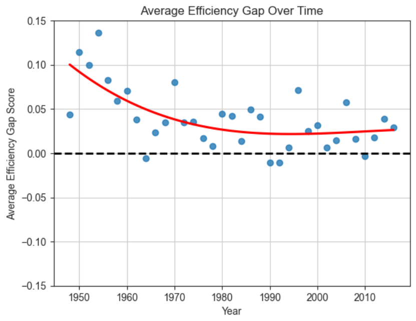
Metric Tracking: Measuring metrics during training/testing to identify underfitting/overfitting

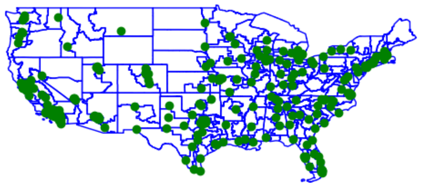
Hyperparameter Tuning: Finding best hyperparameters for training output

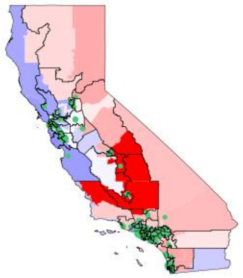
Prediction Maps: Recreating maps for 2021 redistricting

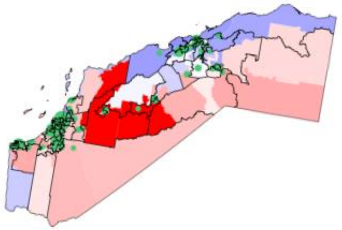
Making Predictions: Using best model to find outcomes

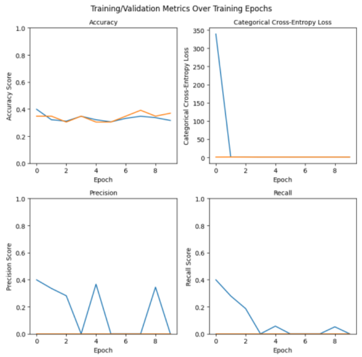
Takeaways: Learnings & Future improvements

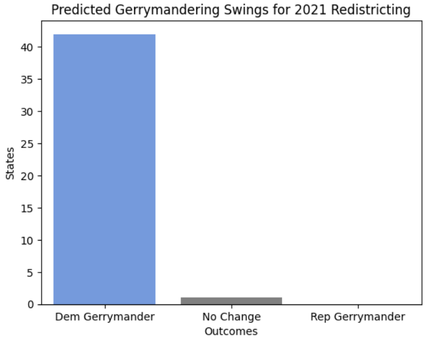




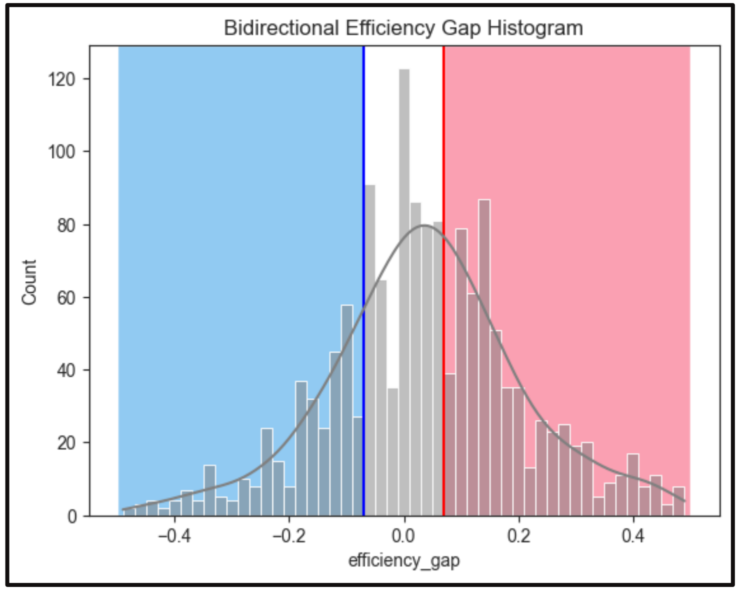


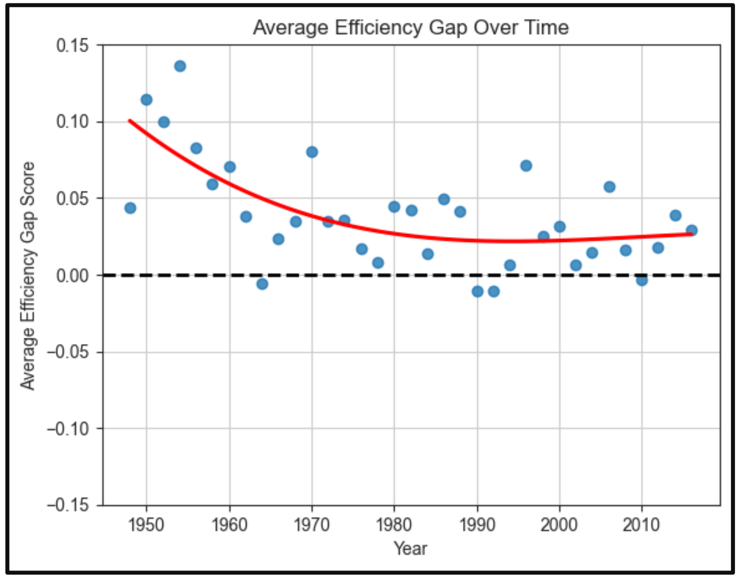






EDA process highlights vast degrees of equal gerrymandering by both parties





Finding 1:
Most states are gerrymandered

62.2% of all state congressional boundaries over the last 70 years are gerrymandered; 39.4% by Republicans and 22.7% by Democrats.

Finding 2:
Democrats increasingly gerrymander since 1960s

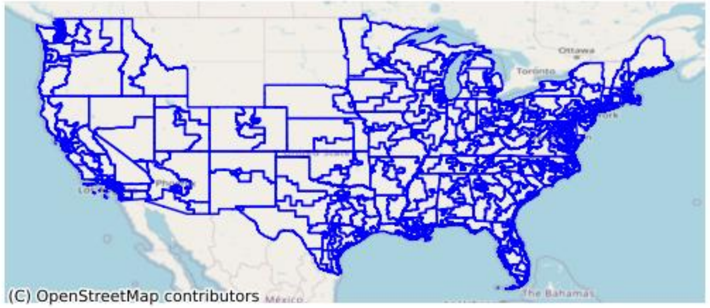
Average efficiency gap decreases over late 20th century, indicating Democrats increasing willingness to gerrymander to same degree as Republicans.

Finding 3:
Redistricting creates equal outcomes for both parties

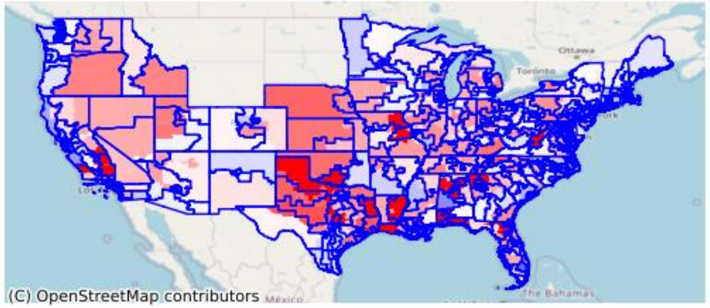
Redistricting statistically results in roughly equal chances for either party to significantly gerrymander in their favor, or with negligent changes in partisanship.

Feature Engineering – creating maps for CNNs to train on

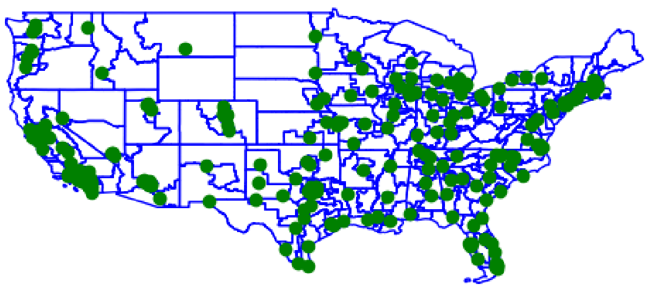
Layer 1: Map Redistricted Boundaries



Layer 2: Overlay Past Voting Results

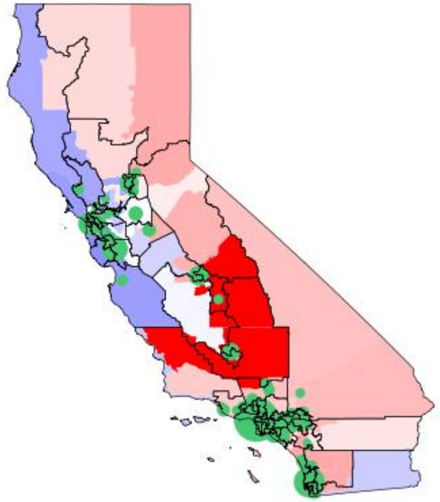


Layer 3: Highlight Population Centers



Combine Layers into Final Map

Example: California after 2011 Redistricting



Efficiency Gap Swing: +0.01 (1% in favor of Republicans)

342 maps created (all instances of redistricting between 1950-2016), tagged with **efficiency gap swings** (swings in efficiency gap after redistricting)

Building a CNN

Goal: Train a convolutional neural network (CNN) on redistricted congressional district maps to evaluate the presence and partisanship of gerrymandering in 2021 congressional districts

Model Design

Input: Standardized Maps (400x400, 200 dpi) – balance between size (complexity) and clarity
Output: Multiclass Classification – input CNN → hidden CNN → Dense layer → Softmax output
Output Classes: Pro-Dem *(swing < -0.05)*, No Change *(-0.05 < swing < 0.05)*, Pro-Rep *(swing > 0.05)*

Model Assumptions

Data Assumptions:

(1) House elections mirror presidential elections
(2) Gerrymandering patterns stationary over time

Model (CNN) Assumptions:

(1) Spatial Hierarchy: Pattern granularity increases
(2) Translation-Invariance: Consistent patterns

Model Metrics

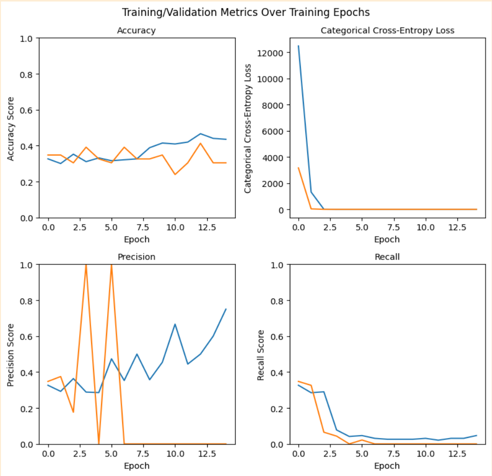
(Primary) Accuracy: Proportion of total correct predictions
Precision: Proportion of all predictions per class that are correct
Recall: Proportion of correct predictions per class

Tuning Techniques

Class Imbalance: Oversample augmented images for minority classes, Cost-sensitive learning weights
Underfitting: Increase model kernels/introduce complex architectures to capture underlying trends
Overfitting: Random dropout on CNN/Dense layers, early stopping when test/validation metrics diverge

Training process was ineffective at improving model metrics

1 Baseline Model

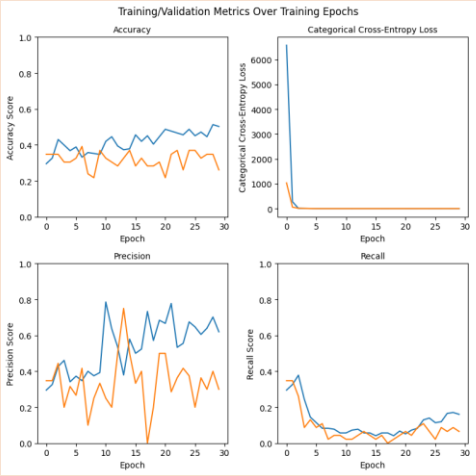


Goal: Set baseline metrics to improve upon

Accuracy: 34.9%
Precision: 19.4%
Recall: 40%

Model was underfit - could not differentiate from random chance

2 Hyperparameter Tuning

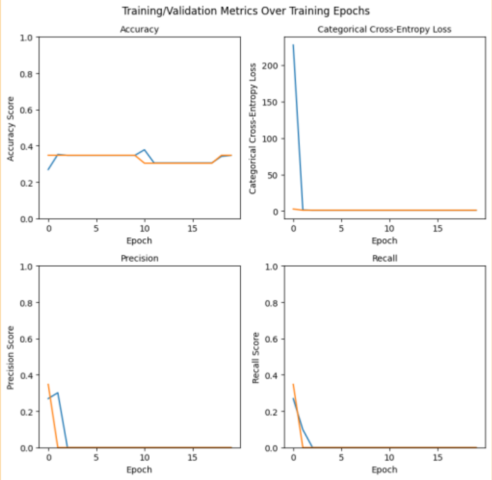


Goal: Find best set of hyperparameters to train CNN

Kernel Window: No effect
Activation Function: No effect
Batch Size: No effect
No. Epochs: No effect

Varying tested parameters had no effect on model metrics

3 Improved Complexity Model

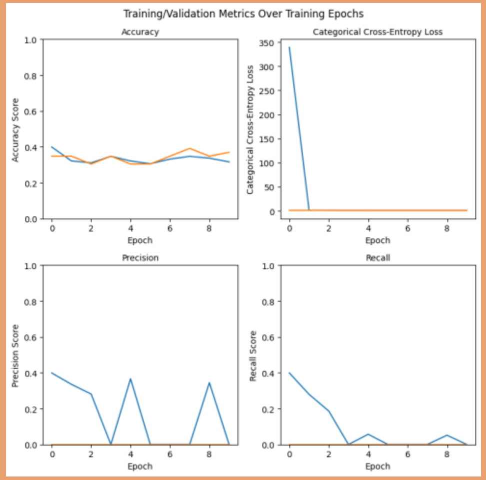


Goal: Increase no. of kernels to reduce underfit

Accuracy: 31.1%
Precision: 0.0%
Recall: 0.0%

Model was still underfit – precision/recall drops as model picks up bias

4 Stacked CNN Layers

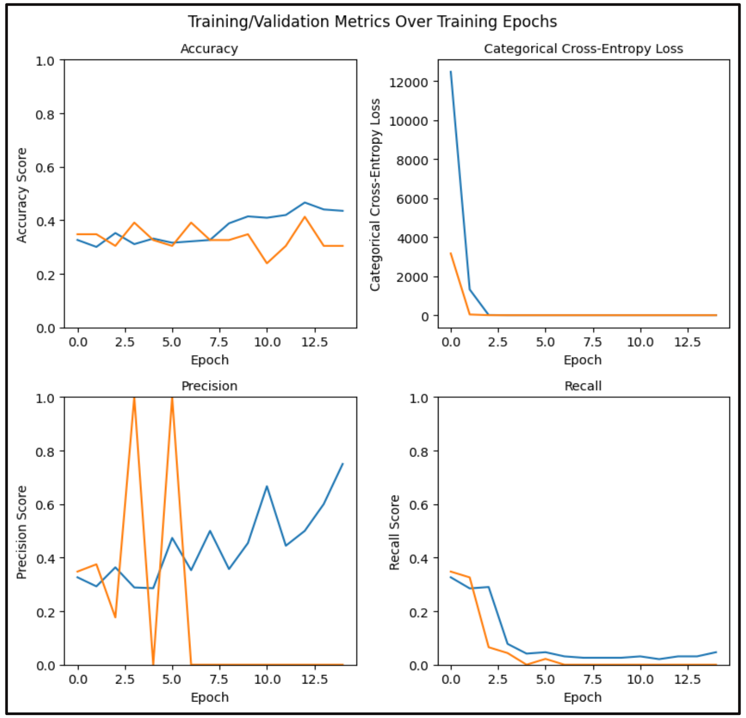


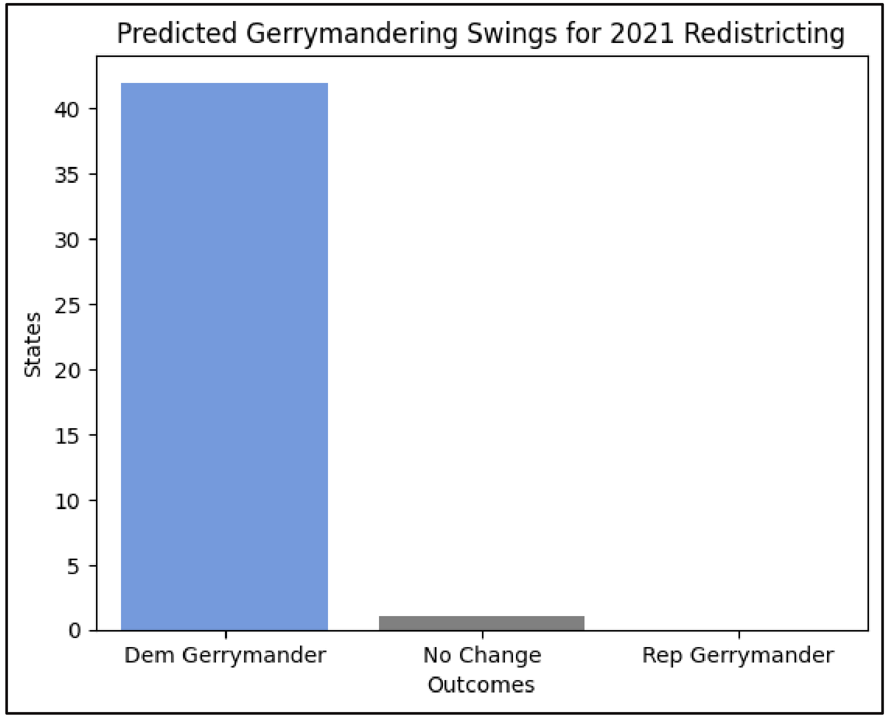
Goal: Stack CNN layers to better transfer relationship between layers

Accuracy: 30.1%
Precision: 0.0%
Recall: 0.0%

Worst-performing model – increased complexity not working (potential bias)

Results: Predictions could not produce expected outcomes





Best Model: Baseline Model (34.4% Accuracy)

Improvements did not yield training improvements as expected – **testing performance was bad for all models** (essentially performing similar to random chance)

Model **exhibited slight overfitting** after 7 epochs – **did not test dropout/early stop** to prevent overfit since model performance was still poor

Prediction Results: 42 Dem Favor (98%), 1 No Change (2%), 0 Rep Favor (0%) – Net D+82

Actual: FiveThirtyEight[1] predicted a D+6 result, sole No Change state (TX) is under litigation for pro-Republican gerrymandering[2]

Model likely picked up on pro-Democratic bias, and could not capture nuance/reasoning behind gerrymander on map results

(1) FiveThirtyEight: What Redistricting Looks Like In Every State (2) All About Redistricting

Takeaways & Future Improvements

Issue	Takeaways	Future Improvements
Model Tuning	**Ineffective Models** **Limited testing** of possible parameters/architectures **given lack of resources on local machine** led to poor training process	**Utilizing Cloud Computing** Using **cloud computing** resources can allow me to **train complex models** on high-quality maps with increased **computational complexity**
Low-Quality Maps	**Poor Map Quality** Available data on congressional voting was **low-quality and inconsistent**, making it difficult to create **holistic maps** that matched voting landscape	**Improving Data Availability** Increased efforts to collect and compile available **demographic and voting trends** over time can help make higher-quality, holistic maps
Small Sample Size	**Small Map Sample** Only **342** redistricting maps were available, leading to **small sample size** prone to **inherent bias** and **high noise-to-signal ratio**	**Generating "What-If" Maps** Writing non-partisan programs to generate **hypothetical boundaries** (with accurate results) can **increase sample size** without bias or overfitting