“THE FINAL COUNTDOWN” – ROCKET LAUNCH SUCCESS PREDICTOR

ADEM CAN & DARIM SHAMSI

BACKGROUND

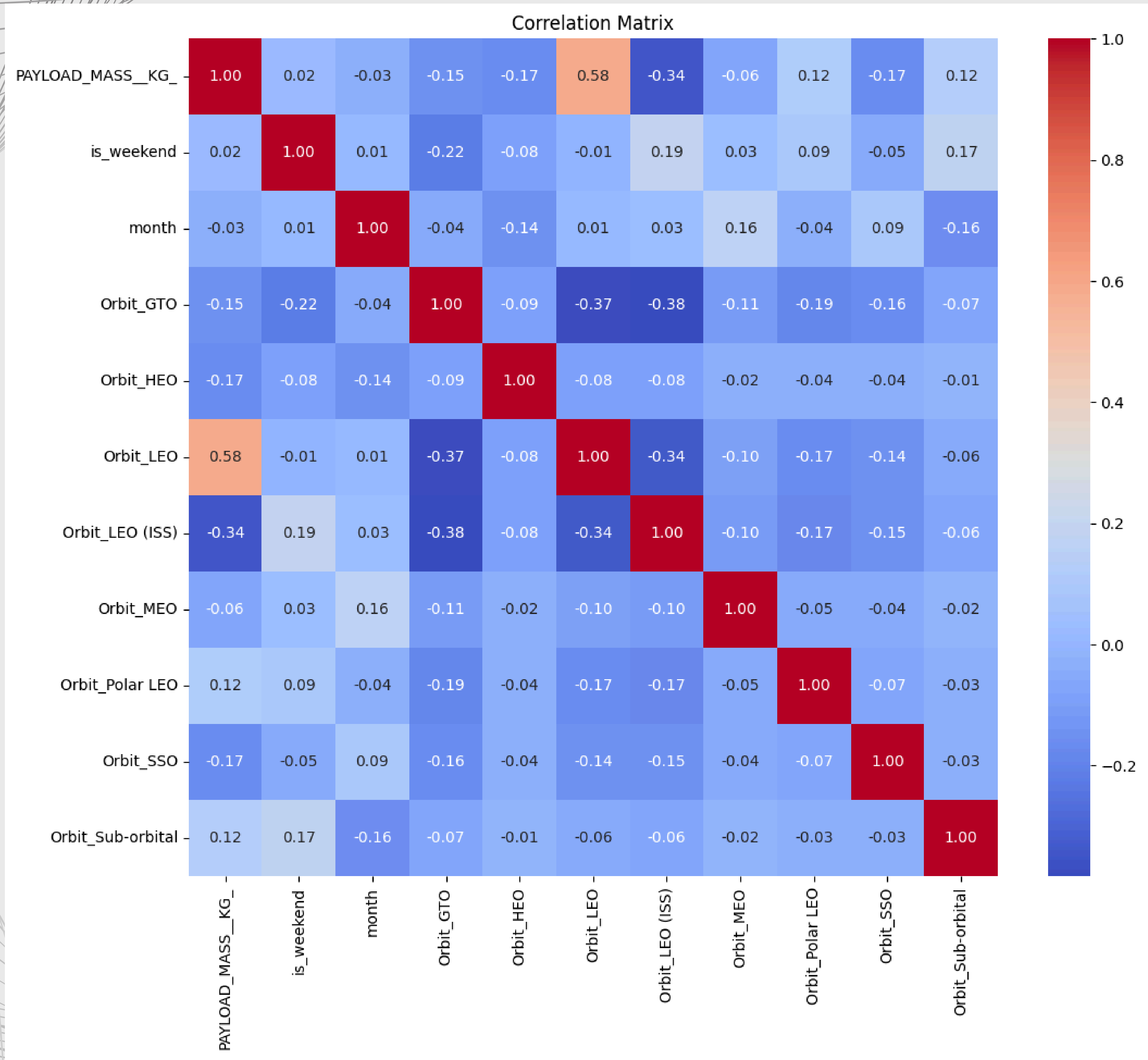
1. **Objective**: Predict the landing outcome (success/failure/no-attempt) of historic rocket launches using launch information
    a. Features like: Launch Location/Time, Payload, Target Orbit
2. **Why:** Predicting if a rocket landing is successful ahead of time can prevent avoidable accidents and save lots of money
    a. The failed 2015 Falcon 9 landing cost SpaceX 260 million $
    b. The latest SpaceX rockets cost 60-100 million $ per launch
3. **Approach:** Machine Learning classification

THE DATA

- **101 Data Points**
- **Location, Time, Launch Information, etc**
- **All mission outcomes were Success**
- **Landing outcome was chosen as classification target**

	Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing _Outcome
0	04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	08-12-2010	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of...	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2	22-05-2012	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
3	08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

FEATURE SELECTION



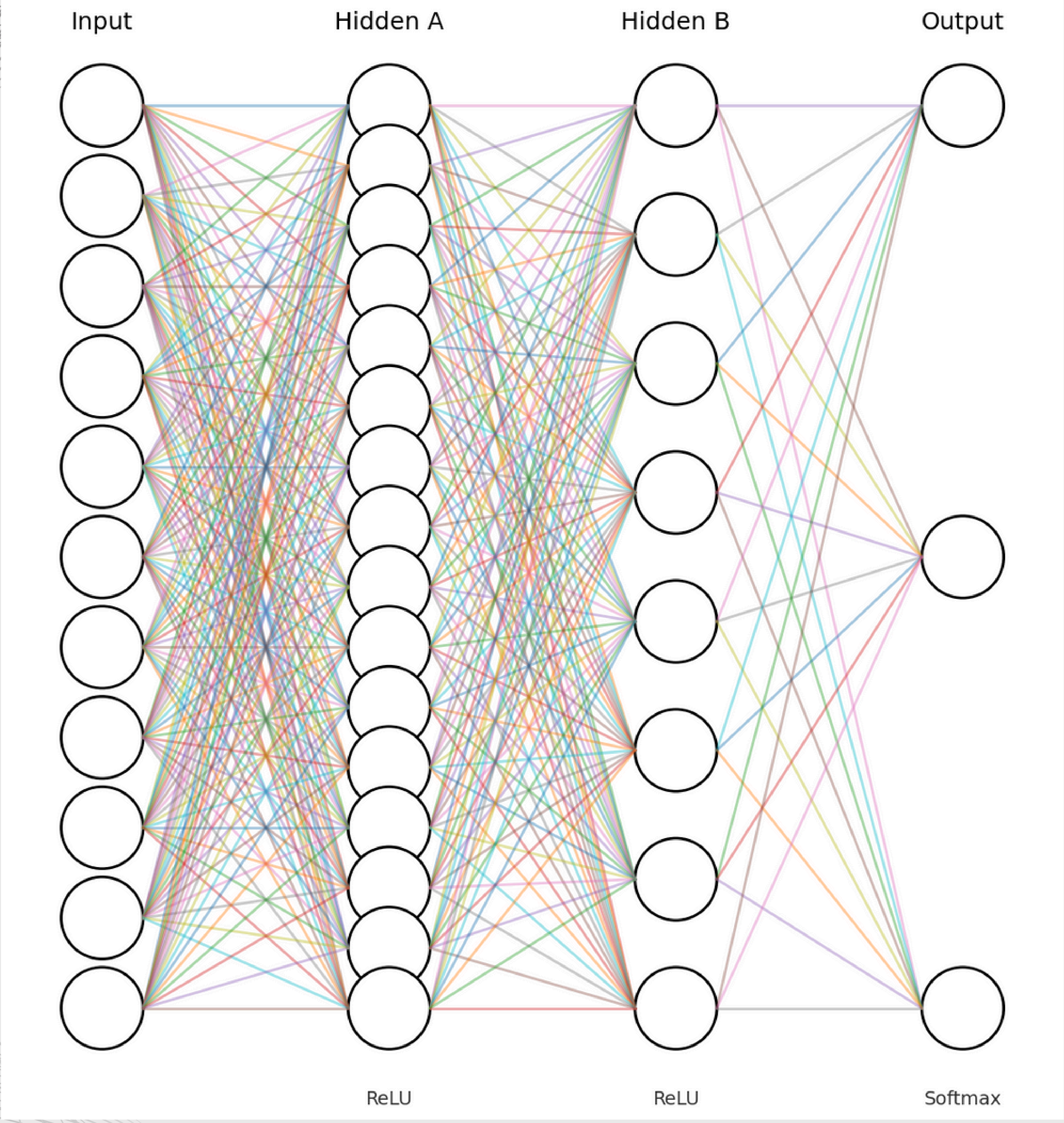
Chosen Features:

- Payload Mass
- Is_Weekend
- Month Launched
- Target Orbit

Rejected Features:

- Booster Version
- Launch Site
- Launch Customer
- Payload Type

MODEL ARCHITECTURE

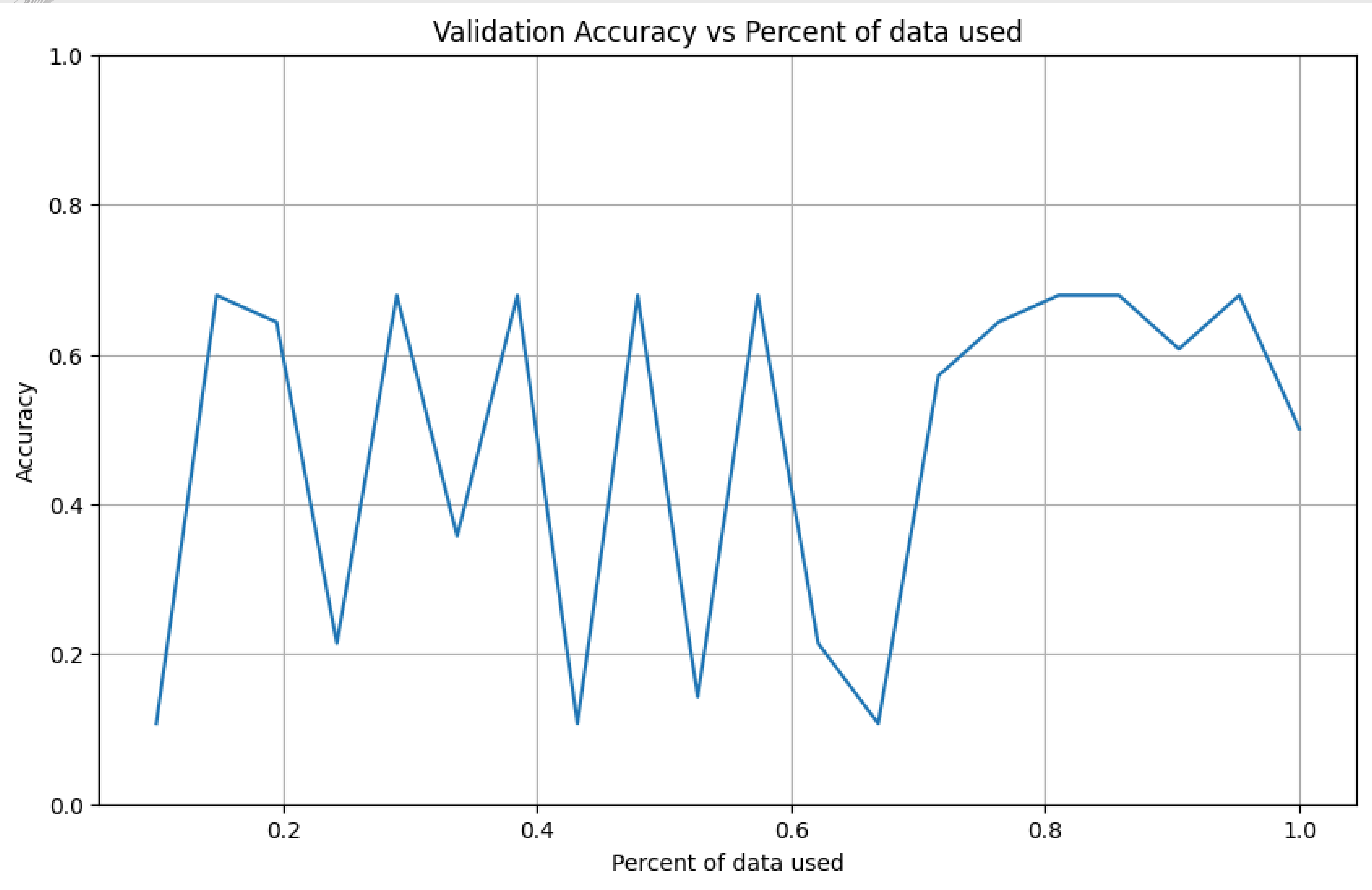


- Model Type: Dense feed-forward neural network with 4 layers (input, 2 hidden, output).
- 11 input features → 3 output classes (success, failure, no-attempt).
- 2 layers with 16 and 8 neurons, using ReLU activation.
- Cross-entropy loss with Adam optimizer for adaptive learning.

TRAINING STRUCTURE

- 60% Train, 30% Test, 10% Validation
- Mini Batch Training (Average Gradients over 8 Training Examples)
- Early Stopping when F1 Score Stops Increasing over Epochs
- 100 Max Epochs

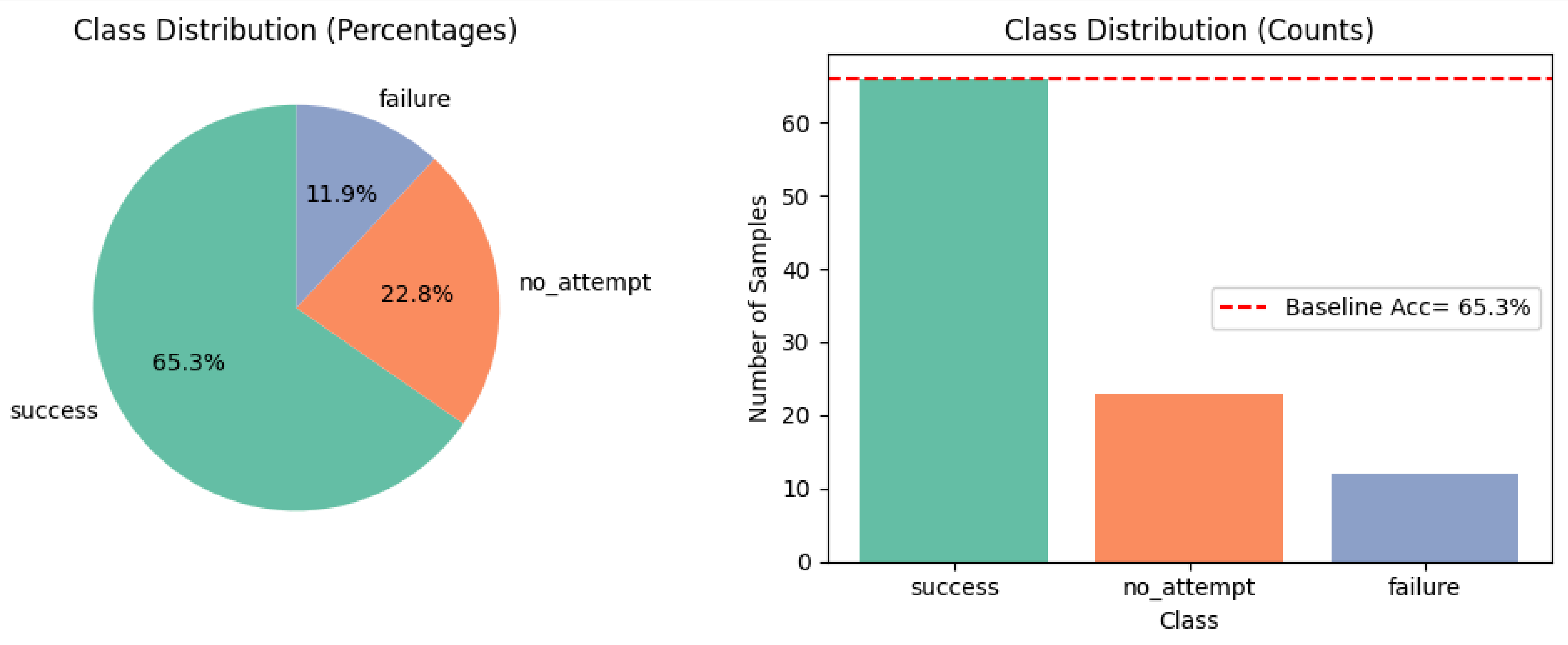
Major Problem: Not Enough Data



- As percentage of data used increases, the accuracy does not increase
- With enough data, the accuracy would eventually increase, not plateau

Major Problem #2: Imbalanced Dataset

Imbalanced Class Distribution:



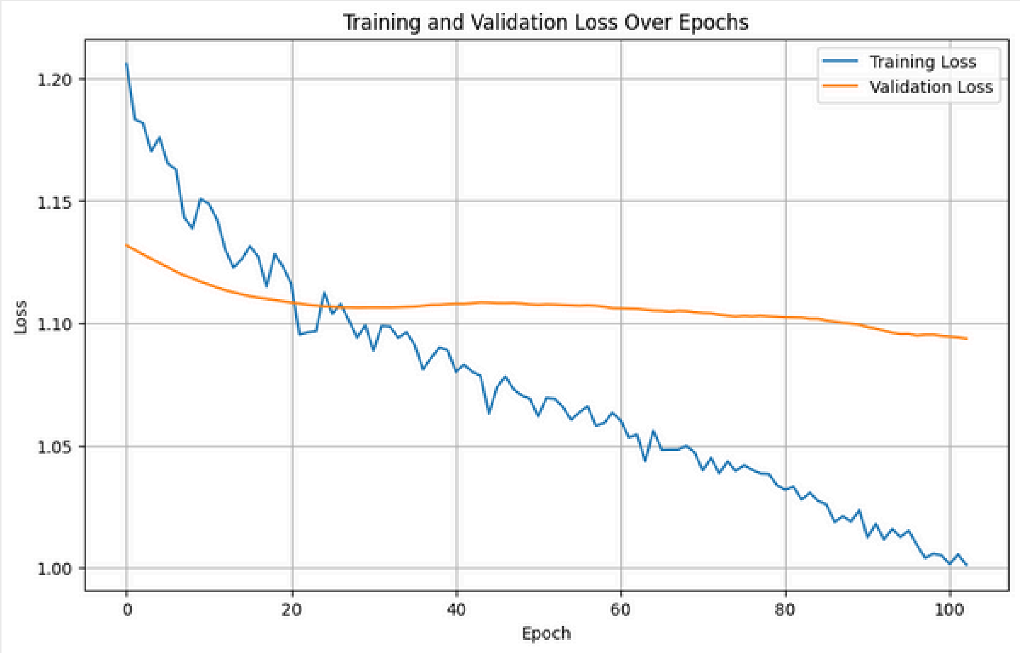
- 65% of the data is only one class
- This means that the model could “learn” to always pick that class and get a baseline 65% accuracy
- This poses a problem in detecting minority classes (Eg: Failure/No-Attempt)

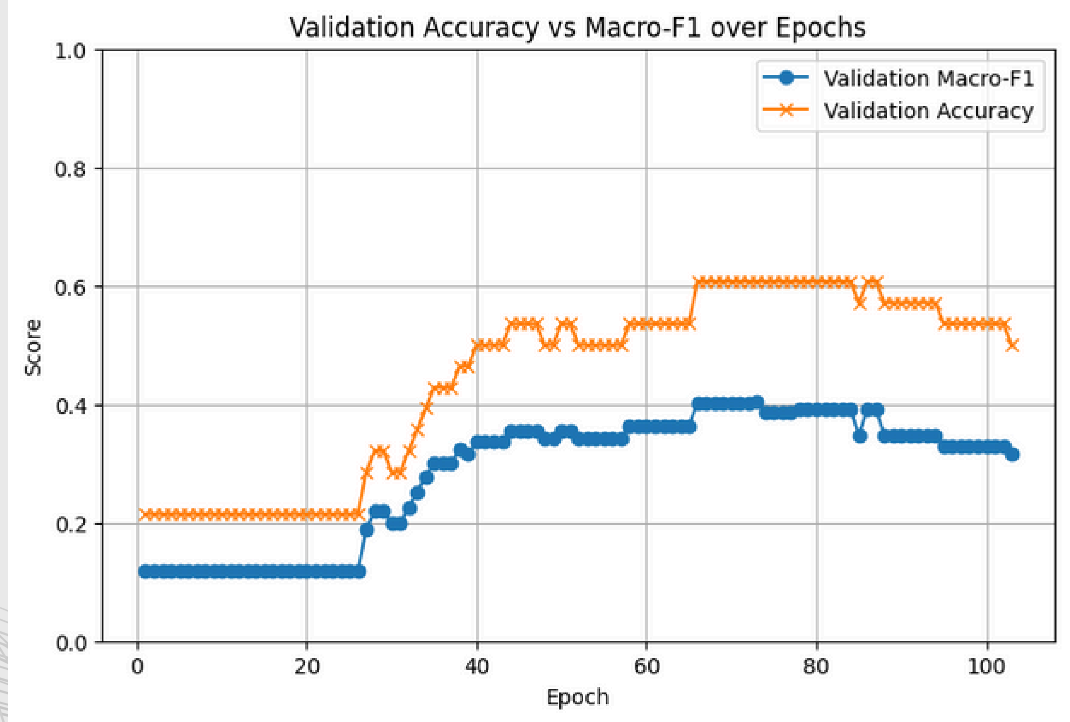
Class Balancing

- To Fix this, class balancing can be introduced
- Class balancing is where you adjust the learning rate between minority and majority classes to account for the imbalance
- Class Weights are calculated based on the data distribution

Training Curves + F1 Score

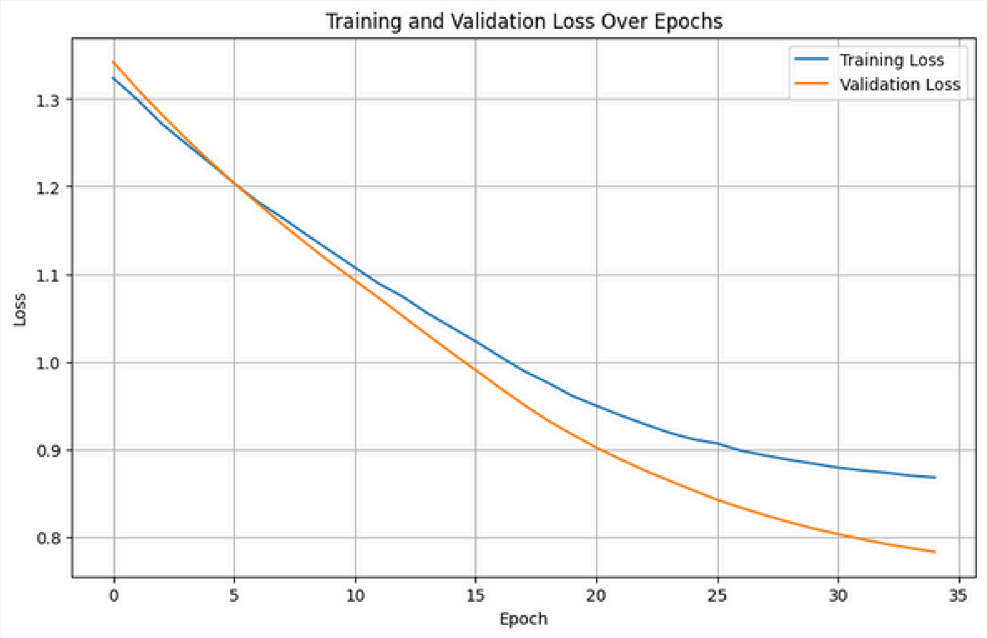
Class Balancing

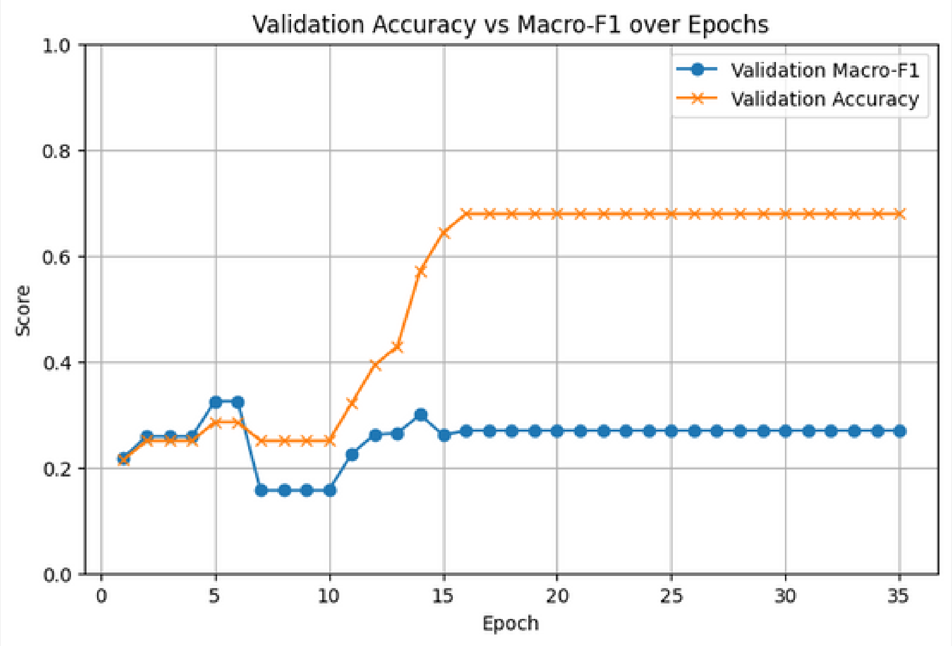




- F1 Score only increases with class balancing
- Training curve smoothness is very different
- The model with no class balancing is clearly “cheating” in some way

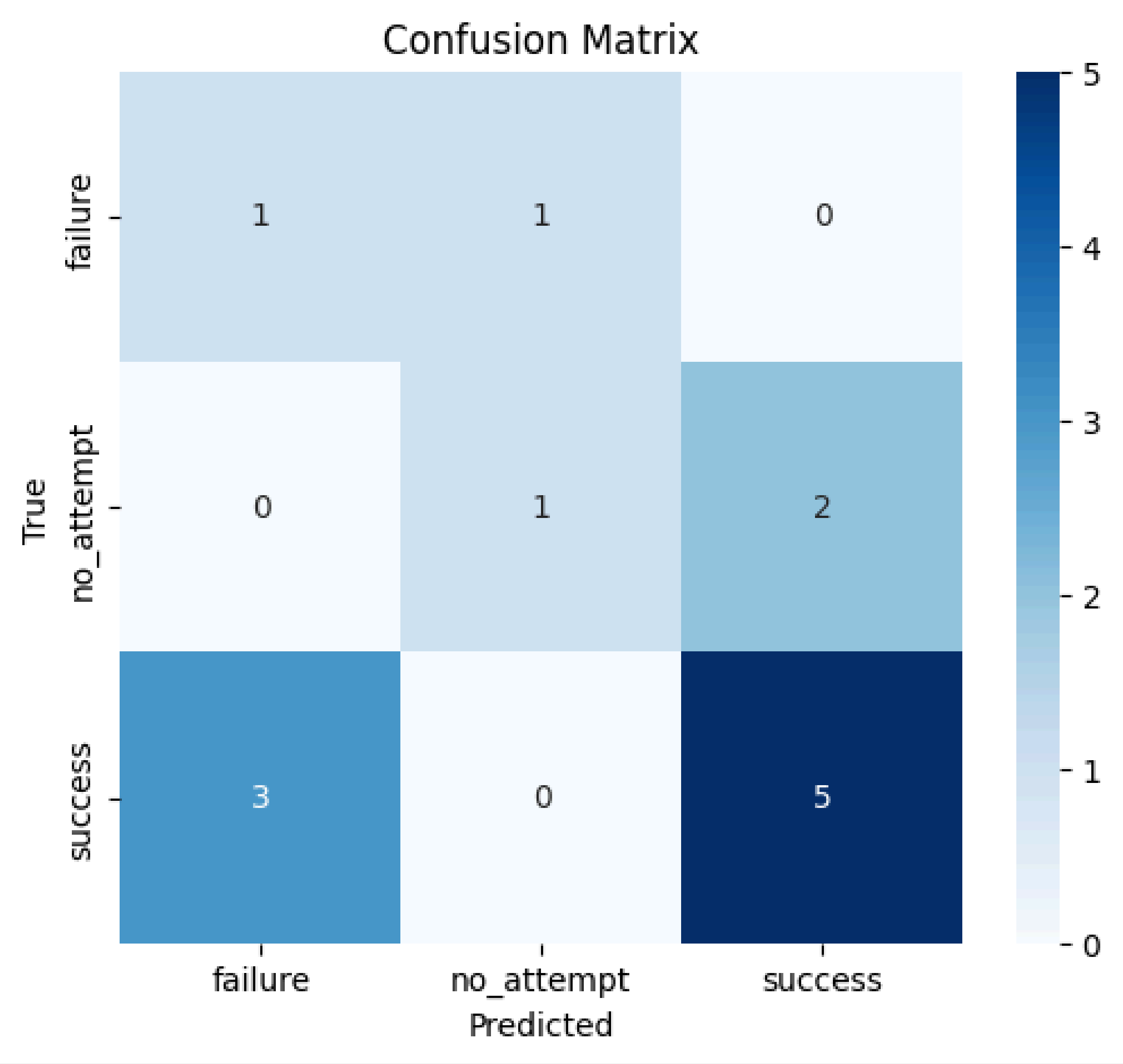
No Class Balancing



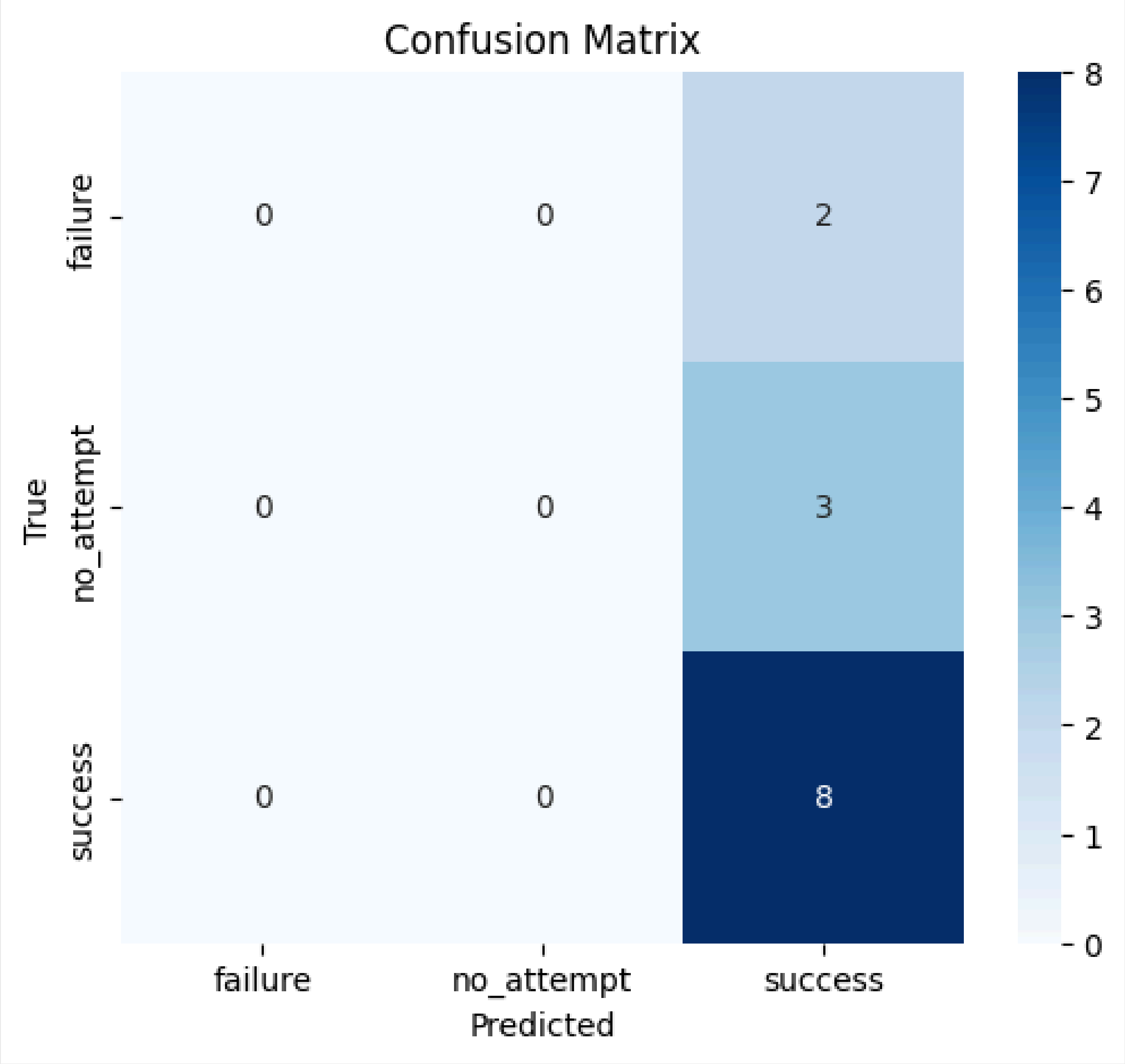


CONFUSION MATRIX

Class Balancing



No Class Balancing



Summary

- Goal: Predicted the outcome of historic rocket launches (success/failure/no-attempt) using metadata from the Space Launch Archive (SpaceX Data).
- Features Used: Payload mass, launch timing (month, weekend), and target orbit.
- Approach: Machine Learning classification with a neural architecture (2 hidden layers, ReLU activation, Adam optimizer).
- Training: 60/30/10 split (train/test/validation), mini-batch training, early stopping, F1-based evaluation.

Challenges:

- Highly imbalanced dataset (most missions successful).
- Limited data points (101), leading to plateaued accuracy despite increased training data usage.

Findings:

- Payload mass and orbit selection proved most influential.
- Class balancing significantly impacted performance (accuracy vs F1 tradeoff).
- Takeaway: With richer, balanced data and inclusion of external features (e.g., weather, policies), predictive accuracy can be improved—making this model a strong foundation for future rocket launch success prediction research.

THANK YOU