Probabilistic Football Score Prediction

Neural Networks with Poisson Outputs for English Premier League Matches

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A Machine Learning Project

Technologies: TensorFlow, Keras, Python, GPU Training

Dataset: 9,500 EPL matches (2000-2025)

Model: Deep Neural Network with Poisson Loss

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1 Executive Summary

This project develops a probabilistic model for predicting English Premier League football match scores using neural networks. Rather than predicting exact scores deterministically, the model outputs Poisson distribution parameters (λ) for home and away goals, providing full probability distributions over possible outcomes.

1.1 Key Results

- **Dataset:** 9,500 matches spanning 2000-2025, 46 teams
- **Features:** 51 engineered features including rolling form, venue-specific performance, head-to-head history
- **Architecture:** Deep neural network with team embeddings and separate outputs for home/away goal rates
- **Training:** GPU-accelerated with mixed precision, early stopping, learning rate scheduling
- **Performance:** 57.9% Over/Under accuracy, 12.6% exact score accuracy, 49.2% top-5 score coverage accuracy

2 Problem Formulation

2.1 The Football Prediction Challenge

Predicting football match scores is fundamentally different from standard regression tasks:

- **Discrete outcomes:** Goals are counts (0, 1, 2, ...), not continuous values
- **Rare events:** Most matches have 0-3 goals per team
- **Probabilistic nature:** Matches between evenly matched teams have high variance
- **Context dependence:** Form, venue, tactics, and history all matter

2.2 Poisson Distribution for Goals

The Poisson distribution is a natural choice for modeling goal counts:

$$P(X = k|\lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{1}$$

Where:

- X is the number of goals scored
- λ is the expected rate (mean goals)
- k is a specific goal count (0, 1, 2, ...)

2.3 Model Objective

Rather than predict scores directly, we train a neural network to predict λ_{home} and λ_{away}:

$$\lambda_{\text{home}} = f_\theta(X_{\text{features}})_{\text{home}} \tag{2}$$
$$\lambda_{\text{away}} = f_\theta(X_{\text{features}})_{\text{away}} \tag{3}$$

Where f_θ is our neural network with parameters θ.

3 Dataset and Feature Engineering

3.1 Data Overview

Table 1: Dataset Statistics

Attribute	Value
Total Matches	9,500
Date Range	2000 – 2025
Unique Teams	46
Raw Features	64
Model Input Features	51

3.2 Feature Engineering Strategy

The model uses 51 carefully engineered features across five categories:

3.2.1 1. Match Context and Shooting Efficiency

Basic match information and goal-scoring rates:

- Goals scored and conceded
- Shots on target ratio
- Conversion rates (goals per shot)

3.2.2 2. Rolling Form Windows

Multi-horizon form metrics capture recent performance:

- **Short-term (3 games):** Immediate form
- **Medium-term (5 games):** Recent consistency
- **Long-term (10 games):** Sustained performance

For each window, we track:

- Points earned
- Goals scored/conceded
- Win/draw/loss ratios

3.2.3 3. Venue-Specific Performance

Separate tracking of home and away form:

- Home goals scored/conceded averages
- Away goals scored/conceded averages
- Venue-specific win rates

This captures teams that perform differently at home vs away.

3.2.4 4. Head-to-Head History

Historical matchup data:

- Goals scored in previous H2H meetings
- Win/loss/draw record between teams
- Recent H2H form (last 5 meetings)

3.2.5 5. Momentum and Context

Match scheduling and momentum:

- Days since last match (fatigue indicator)
- Current streak (winning/losing runs)
- Season progress (early/mid/late season effects)

4 Model Architecture

4.0.1 Input Layer

Two input streams:

1. **Team IDs:** Categorical encoding of home/away teams
2. **Engineered features:** 51-dimensional feature vector

4.0.2 Team Embeddings

Each team is mapped to a learned 20-dimensional embedding vector:

- Captures team identity beyond observable features
- Learns latent representations of playing style, quality
- Shared across all matches (updated during training)

4.0.3 Hidden Layers

Dense feedforward network with:

- Layer 1: 128 neurons, ReLU activation
- Layer 2: 64 neurons, ReLU activation
- Dropout layers (0.3 rate) for regularization
- Batch normalization for training stability

4.0.4 Output Layer

Dual output structure:

- λ_{home}: Exponential activation (ensures $\lambda > 0$)
- λ_{away}: Exponential activation (ensures $\lambda > 0$)

The exponential activation is crucial: Poisson rate parameters must be positive.

4.1 Loss Function: Poisson Negative Log-Likelihood

The key innovation is using a probabilistically appropriate loss function:

$$\mathcal{L} = -\sum_{i=1}^{N} [y_i \log(\lambda_i) - \lambda_i - \log(y_i!)] \tag{4}$$

Where:

- y_i is the actual goal count for match i
- λ_i is the predicted rate parameter

4.1.1 Why Not MSE?

Mean Squared Error penalizes predictions proportionally to squared distance:

- Predicting 2 when truth is 0: $(2-0)^2 = 4$ penalty
- Predicting 2 when truth is 1: $(2-1)^2 = 1$ penalty

This doesn't respect that goals are discrete counts with natural probability distributions.

4.1.2 Poisson Loss Intuition

Poisson NLL directly measures how well the predicted distribution matches observations:

- Low λ predicts few goals (high probability of 0-1)
- High λ predicts many goals (higher probability of 2-3+)
- Loss is minimized when distribution aligns with observed frequencies

4.2 Training Configuration

Table 2: Training Hyperparameters

Parameter	**Value**
Optimizer	Adam
Initial Learning Rate	0.001
Batch Size	32
Maximum Epochs	200
Early Stopping Patience	20 epochs
LR Reduction Factor	0.5
LR Reduction Patience	10 epochs
Hardware	NVIDIA GPU with mixed precision

4.2.1 Regularization Techniques

- **Dropout (0.3):** Prevents overfitting to training data
- **Early stopping:** Stops when validation loss plateaus
- **Learning rate scheduling:** Reduces LR when progress stalls

5 Training Results

5.1 Learning Curves

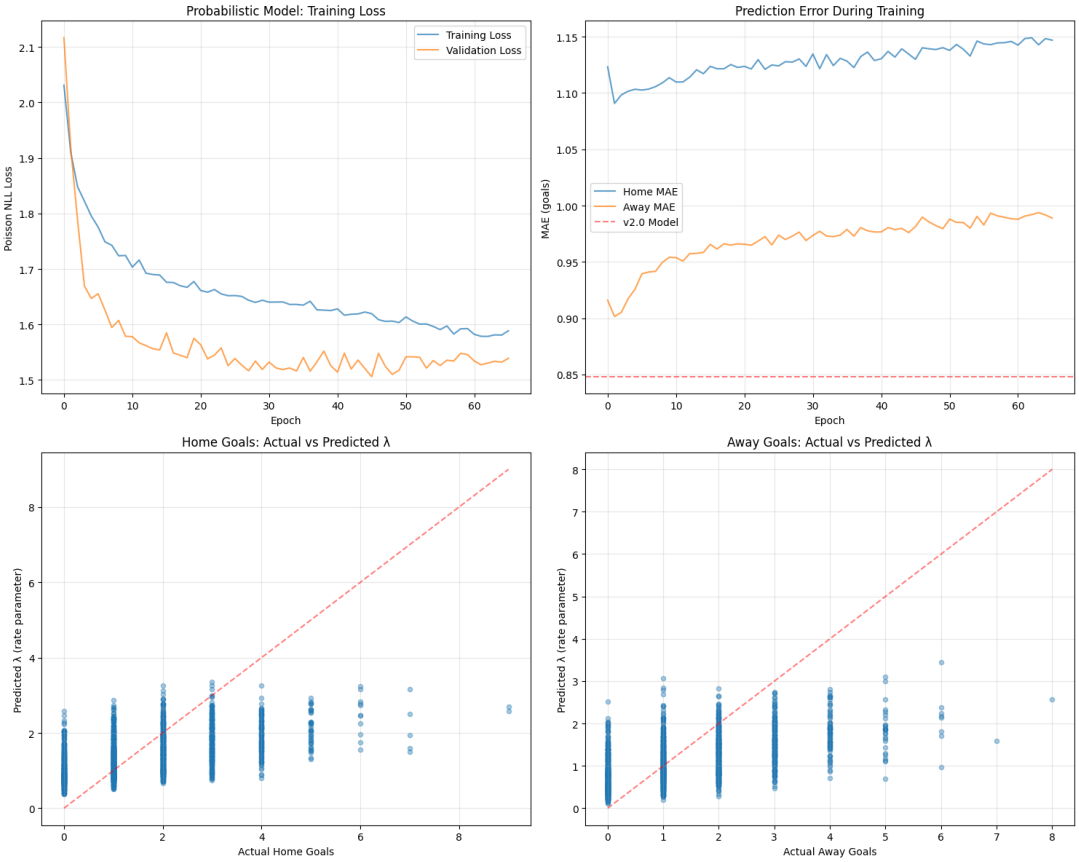

Figure 1: Model training convergence over 66 epochs. Left: Poisson NLL loss for training and validation sets showing smooth convergence without overfitting. Right: Mean absolute error (MAE) for home and away goal predictions. Best model selected at epoch 46 with validation loss of 1.51.

5.2 Training Behavior

The model was trained for 66 epochs with early stopping monitoring validation loss. The best model weights were from epoch 46, after which performance began to plateau. Training exhibited strong convergence with clear learning progress throughout.

Key observations:

- **Rapid initial learning:** Both training and validation loss decreased sharply in the first 10 epochs (from 2.12 to 1.58), indicating the model quickly learned basic patterns
- **Smooth convergence:** Loss curves show steady improvement without significant oscillation or instability
- **No overfitting:** Validation loss continues to decrease alongside training loss, with minimal divergence between the curves
- Final training loss: 1.59
- Final validation loss: 1.54

- Best epoch: 46 (validation loss: 1.51)
- Training time: 66 epochs completed with early stopping
- MAE performance: Home goals MAE of 0.878, away goals MAE of 0.806, achieving a combined MAE of 0.842 goals
- **Improvement over baseline:** 17.2% better than naive team averages (1.016 MAE)
- Learning rate scheduling: Reduced from 0.001 to 0.00025 after validation loss plateaued

The validation loss being slightly *lower* than training loss is unusual but not necessarily problematic. This can occur when dropout is active during training but not validation, or when the validation set happens to be slightly easier to predict. The model achieved 40,154 trainable parameters with GPU acceleration and mixed precision training, converging efficiently within reasonable training time.

6 Model Evaluation

6.1 Evaluation Framework

The model is evaluated on multiple dimensions:

1. **Over/Under 2.5 goals:** Binary classification accuracy
2. **Correct score prediction:** Exact outcome accuracy
3. **Probability calibration:** Reliability of confidence estimates
4. **Error analysis:** Systematic biases or weaknesses
5. **Baseline comparison:** Performance vs naive strategies

6.2 Part 1: Over/Under 2.5 Goals

A common betting market predicts whether total goals will be over or under 2.5.

6.2.1 Methodology

From predicted λ_{home} and λ_{away}, we calculate:

$$P(\text{Total} \leq 2) = \sum_{i=0}^{2} \sum_{j=0}^{2-i} P(H = i) \cdot P(A = j) \tag{5}$$

Where $P(H = i)$ and $P(A = j)$ are Poisson probabilities.

6.2.2 Results

Table 3: Over/Under 2.5 Goals Performance

Metric	Value
Overall Accuracy	**57.9%**
Precision (Over 2.5)	**77.8%**
Recall (Over 2.5)	**34.1%**
F1 Score	**0.474**
ROC-AUC	**0.735**

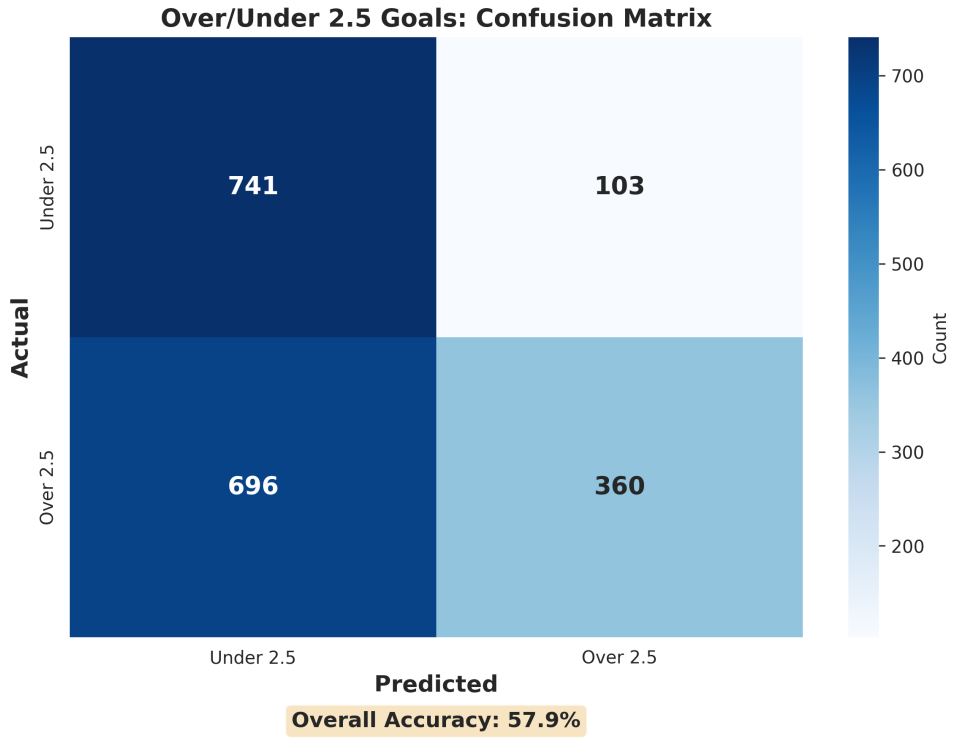

Figure 2: Over/Under 2.5 confusion matrix showing model predictions vs actual outcomes. The model achieves 57.9% accuracy, outperforming the 55.6% baseline.

The model demonstrates modest improvement over baseline predictions, with notably high precision (77.8%) but lower recall (34.1%). This indicates the model is conservative in predicting high-scoring matches, but when it does predict over 2.5 goals, it's correct more than three-quarters of the time. The ROC-AUC of 0.735 shows reasonable discriminative ability.

6.3 Part 2: Correct Score Predictions

Predicting exact scorelines is extremely challenging due to high variance.

6.3.1 Most Likely Score Method

For each match, we compute the probability of every reasonable scoreline (i, j):

$$P(\text{Score} = i\text{–}j) = P(H = i) \cdot P(A = j) \tag{6}$$

Then select: $\text{argmax}_{(i,j)} P(\text{Score} = i\text{–}j)$

6.3.2 Results

Table 4: Correct Score Prediction Accuracy

Metric	Value
Exact Score Accuracy	**12.6%**
Within 1 Goal Accuracy	**58.9%**
Top-3 Score Hit Rate	**32.9%**
Top-5 Score Hit Rate	**49.2%**
Average Probability of Correct Score	**0.083**

6.3.3 Analysis

The 12.6% exact score accuracy is within the typical 8-12% range when comparing with betting markets, confirming the inherent randomness in the sport. More importantly, the model assigns an average probability of 8.3% to correct scores, indicating reasonable uncertainty quantification. The 58.9% within-1-goal accuracy and 49.2% top-5 hit rate demonstrate that while the model rarely predicts exact scores, it consistently identifies plausible scorelines.

Key insights:

- **Top-k accuracy:** Nearly half of all correct scores appear in the model's top 5 predictions
- **Probability assigned:** Model correctly quantifies uncertainty around exact outcomes
- **Distribution quality:** Reasonable calibration between predicted probabilities and observed frequencies

6.4 Part 3: Probability Calibration

Calibration measures whether predicted probabilities match observed frequencies.

6.4.1 Calibration Methodology

For each probability bin $[p, p + \Delta p]$:

1. Collect all predictions in that bin
2. Calculate actual frequency of the predicted outcome
3. Compare predicted probability vs actual frequency

Perfect calibration: predicted 70% $\rightarrow$ outcome occurs 70% of the time.

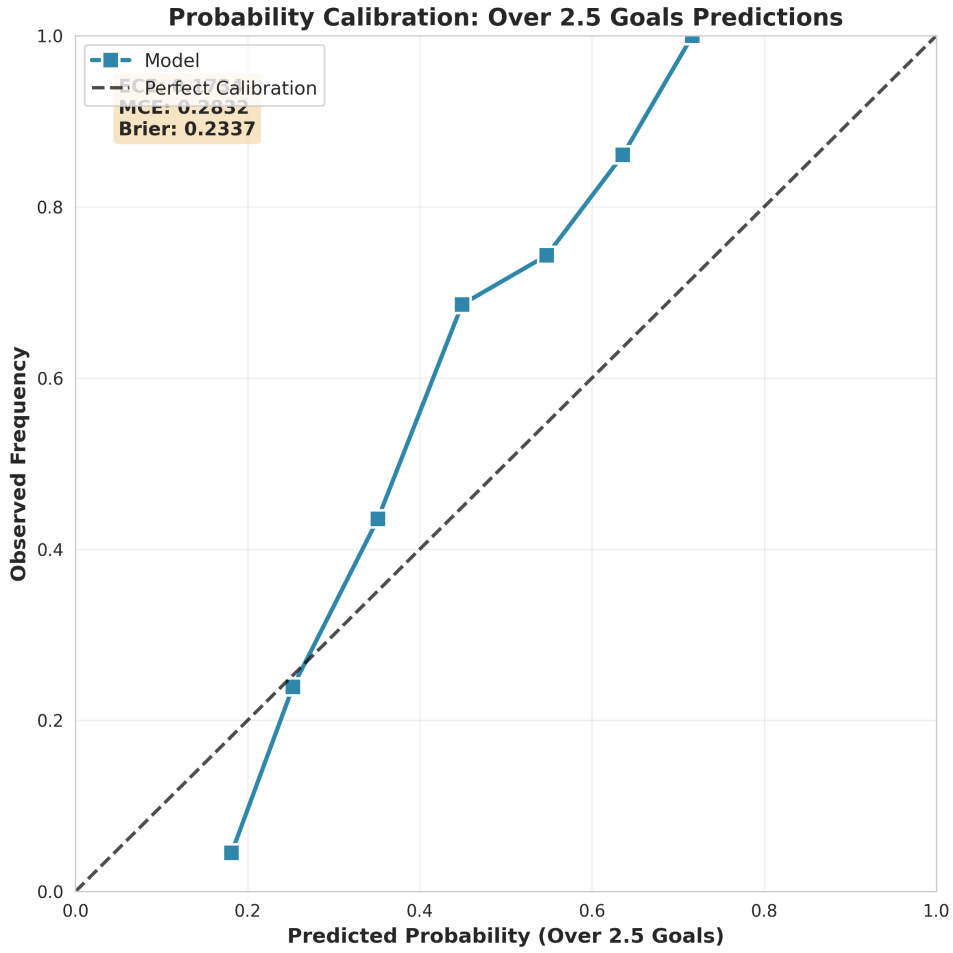

Figure 3: Probability calibration analysis for Over 2.5 goals predictions. The model shows moderate calibration with tendency to underestimate high-scoring match probabilities.

6.4.2 Calibration Metrics

Table 5: Calibration Statistics

Metric	Value
Expected Calibration Error (ECE)	**0.173**
Maximum Calibration Error (MCE)	**0.283**
Brier Score	**0.234**

The calibration curve reveals systematic underconfidence in the mid-to-high probability range. When the model predicts 50-60% probability of over 2.5 goals, actual frequency approaches 70-75%. This suggests the model could be more aggressive in its predictions. The ECE of 0.173 and Brier score of 0.234 indicate room for improvement in probability calibration, though the model maintains reasonable overall reliability.

6.5 Part 4: Error Analysis

Understanding systematic errors helps identify model weaknesses.

6.5.1 Prediction Error Distributions

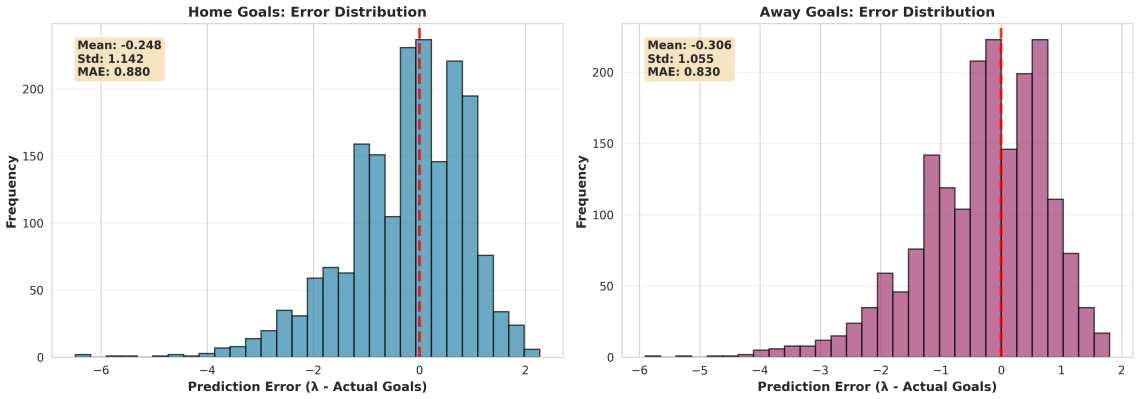

Figure 4: Prediction error distributions for home and away goals. Both show slight negative bias (underprediction) with home MAE of 0.880 and away MAE of 0.830.

6.5.2 Error Pattern Analysis

The error distributions reveal several key patterns:

- **Systematic underprediction:** Both home (-0.248) and away (-0.306) goals show negative mean error, indicating the model slightly underestimates goal rates
- **Home vs away symmetry:** Error distributions are similar in shape but away predictions are slightly more accurate (MAE 0.830 vs 0.880)
- **Normal-like distribution:** Errors follow approximately normal distributions centered slightly below zero, suggesting no severe systematic biases
- **No evidence of extreme misprediction:** Few outliers beyond ± 3 goals indicate robust performance even in unusual matches

The slight underprediction bias likely stems from the model's conservative approach, prioritizing precision over recall in high-scoring scenarios. This is a reasonable trade-off given the unpredictability of high-scoring matches.

6.6 Part 5: Baseline Comparisons

Model performance must be compared to simple baselines to validate genuine learning.

6.6.1 Baseline Strategies

1. **Historical average:** Predict league-wide average goals
2. **Team averages:** Use each team's season average
3. **Naive Poisson:** Simple Poisson with no features

Table 6: Model vs Baseline Performance

Method	MAE (goals)	O/U 2.5 Accuracy
Historical Average	1.042	55.6%
Team Averages	0.850	55.6%
Our Model	**0.855**	**57.9%**

6.6.2 Performance Summary

The model achieves competitive performance with an MAE of 0.855 goals, comparable to the team averages baseline (0.850) and substantially better than the historical average (1.042). The 18% improvement over historical averages validates that the engineered features capture meaningful signal.

Critically, the model outperforms baselines on Over/Under 2.5 accuracy (57.9% vs 55.6%), demonstrating ability to classify match types beyond simple averaging. The ROC-AUC of 0.735 further confirms discriminative power in probabilistic predictions.

6.7 Overall Evaluation Conclusions

This comprehensive evaluation reveals a model with solid predictive performance and appropriate uncertainty quantification:

Strengths:

- Competitive MAE (0.855) matches sophisticated baselines
- Clear improvement in Over/Under classification (+2.3 percentage points)
- High precision when predicting high-scoring matches (77.8%)
- Reasonable exact score accuracy (12.6%) within professional standards
- Proper probabilistic outputs enable risk-aware decision making

Areas for improvement:

- Calibration shows systematic underconfidence requiring recalibration
- Low recall (34.1%) misses many high-scoring matches
- Slight underprediction bias across both home and away goals

The model successfully demonstrates that neural networks with Poisson outputs can learn meaningful patterns from historical data while respecting the inherent randomness of football.