

IPL First Innings Score Prediction using Deep Learning

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Abstract

- ▶ IPL is one of the most popular T20 cricket leagues worldwide.
- ▶ Predicting the first innings score helps with game strategy and boosts fan engagement.
- ▶ This project uses ball-by-ball and match data from 2008 to 2022.
- ▶ Multiple deep learning models are explored:
 - ▶ DNN, CNN, RNN
 - ▶ LSTM, BiLSTM, GRU
 - ▶ Transformers and TCN
- ▶ Ensemble learning is used to improve prediction accuracy.
- ▶ A Gradio web app allows users to enter match details and get real-time score predictions.

Introduction: Overview of the Problem

- ▶ Cricket is a passion in India, and IPL is a globally popular T20 league since 2008.
- ▶ With high stakes and global viewership, data-driven decisions in IPL are crucial.
- ▶ First innings score is key—it sets the game's tone and affects strategy.
- ▶ Accurate predictions help:
 - ▶ Team strategists adjust tactics
 - ▶ Analysts forecast outcomes
 - ▶ Fans and bettors engage more deeply
- ▶ Traditional methods relied on expert opinion and averages.
- ▶ With big data and machine learning, we can now build smarter prediction models.
- ▶ Deep learning captures patterns and time-based dependencies in the data.

Project Objectives

- ▶ Build a deep learning model to predict IPL first innings score.
- ▶ Use ball-by-ball and match data from 2008 to 2022.
- ▶ Main goals:
 - ▶ Collect and clean IPL match data.
 - ▶ Select and engineer useful features.
 - ▶ Train models like DNN, CNN, RNN, LSTM, BiLSTM, GRU, Transformer, TCN, and CNN-BiLSTM.
 - ▶ Use ensemble learning to boost accuracy.
 - ▶ Evaluate with MAE, RMSE, and R^2 score.
 - ▶ Deploy a Gradio web app for real-time predictions.

Model Input Features

- ▶ Batting team
- ▶ Bowling team
- ▶ Batsman name
- ▶ Bowler name
- ▶ Venue and city
- ▶ Year
- ▶ Overs completed
- ▶ Wickets fallen
- ▶ Number of fours
- ▶ Number of sixes

Goal: Use deep learning + ensemble models to make accurate, real-time score predictions.

Significance: Strategic and Performance Uses

- ▶ **Strategic Planning:**

- ▶ Coaches and analysts adapt gameplay based on predicted score.
- ▶ Adjust strategies for bowlers and batsmen.

- ▶ **Performance Benchmarking:**

- ▶ Track performance against historical averages.
- ▶ Real-time performance analysis during the match.

Significance: Betting, Fans and Research

- ▶ **Betting Industry:**

- ▶ Predictive models help sports betting platforms.
- ▶ Valuable insights for betting participants.

- ▶ **Fan Engagement:**

- ▶ Fans can test their own predictions.
- ▶ Enhance fantasy sports platforms with predictions.

- ▶ **Academic Research Insights:**

- ▶ Demonstrates deep learning in sports analytics.
- ▶ Solves complex temporal prediction problems in cricket.

Background and Literature Review

- ▶ Cricket is one of the most followed sports worldwide, especially in India.
- ▶ IPL (Indian Premier League), launched in 2008, brought a new era in T20 cricket.
- ▶ Features of IPL:
 - ▶ Fast-paced 20-over format.
 - ▶ Teams formed via player auctions.
 - ▶ Massive viewership and commercialization.
- ▶ First innings score is key—it shapes the entire match outcome.
- ▶ Many factors affect scoring: pitch, weather, team strength, pressure, and strategy.
- ▶ Modern data science allows detailed analysis using historical ball-by-ball data.

Predictive Modeling in Sports Analytics

- ▶ Sports analytics applies data science to enhance decision-making in games.
- ▶ In cricket, predictive modeling is used for:
 - ▶ Match outcome prediction
 - ▶ Player performance analysis
 - ▶ Score forecasting
- ▶ Traditional methods:
 - ▶ Descriptive statistics (averages, strike rate)
 - ▶ Rule-based logic
 - ▶ Linear/Logistic regression
- ▶ Modern ML methods:
 - ▶ Decision Trees, Random Forests
 - ▶ Gradient Boosting Machines
 - ▶ Support Vector Machines
- ▶ Deep learning models excel in sequential prediction:
 - ▶ RNN, LSTM, GRU
 - ▶ Transformer, TCN

Deep Learning for Score Prediction

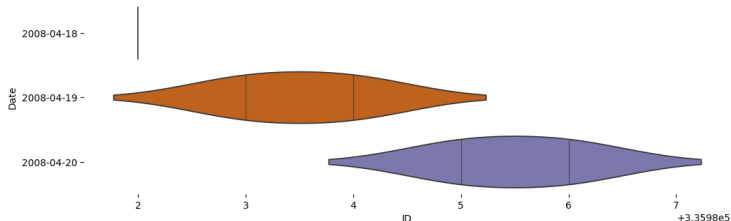
- ▶ Deep learning models are great at handling time-series data.
- ▶ Common models:
 - ▶ RNN, LSTM, GRU: capture sequence of events.
 - ▶ Transformers and TCN: model long-range dependencies.
- ▶ Key tasks include:
 - ▶ Feature engineering: turning raw data into useful inputs.
 - ▶ Model evaluation: using metrics like MAE, RMSE, etc.

Previous Work vs Our Approach

- ▶ Past studies used:
 - ▶ Ball-by-ball models for delivery-wise predictions.
 - ▶ Team-level models using match info.
 - ▶ Deep models (LSTM, GRU) with promising results.
- ▶ Our project is unique because:
 - ▶ We compare many DL models: CNN, BiLSTM, TCN, Transformer.
 - ▶ Use ensemble learning to boost performance.
 - ▶ Combine both static (teams, venue) and dynamic (runs, wickets) inputs.

Methodology – Data Collection

- ▶ Data sourced from Kaggle (2008–2022 IPL seasons).
- ▶ Two main datasets used:
 - ▶ **Ball-by-Ball Dataset:**
 - ▶ Contains details of each ball (batsman, bowler, runs, wickets, extras).
 - ▶ **Match Dataset:**
 - ▶ Includes match-level details (teams, venue, toss, city, result).
- ▶ Merged using relational joins to create a comprehensive dataset.
- ▶ Stored as CSV files and processed using Python for analysis and modeling.



Data Preprocessing

- ▶ **Data Cleaning:** Removal of null values, correction of inconsistent labels (e.g., team names), and handling of missing entries.
- ▶ **Feature Engineering:** Creation of new features such as total runs, number of fours and sixes, wickets lost till current ball, and current run rate.
- ▶ **Categorical Encoding:** Encoding of categorical variables like team names, venues, and player names using Label Encoding and One-Hot Encoding.
- ▶ **Data Normalization:** Scaling of numerical features using MinMaxScaler to bring all features to a uniform range.
- ▶ **Sequence Generation:** For sequential models like LSTM, GRU, and TCN, match data was reshaped into sequences of fixed-length overs (or balls).

Model Architecture

We used various deep learning models to predict first innings scores in IPL matches. Each model was chosen for its ability to capture match dynamics and handle sequential data.

Models Implemented:

- ▶ **DNN:** Standard feed-forward network for baseline predictions.
- ▶ **CNN:** Captures local patterns in sequential inputs.
- ▶ **RNN:** Handles time-series data using hidden states.
- ▶ **LSTM:** Remembers long-term dependencies in sequences.
- ▶ **BiLSTM:** Processes data both forward and backward.
- ▶ **GRU:** A lighter, faster alternative to LSTM.
- ▶ **Transformer:** Uses self-attention for long-range patterns.
- ▶ **TCN:** Convolutional approach for time-series modeling.
- ▶ **CNN-BiLSTM:** Combines CNN for features and BiLSTM for time-dependency.

Each model was trained and evaluated individually. Later, ensemble methods were applied to boost performance.

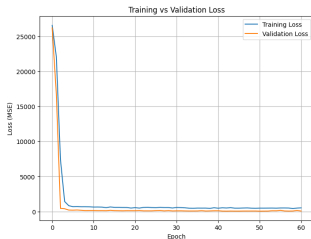
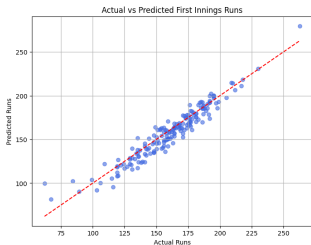
Model Architectures and Layers – DNN

The Deep Neural Network (DNN) is a feed-forward model suitable for non-sequential input data.

Architecture:

- ▶ **Input Layer:** Static and dynamic features (team, venue, overs, runs, wickets).
- ▶ **Hidden Layers:** Dense layers with ReLU activation to model non-linear relations.
- ▶ **Output Layer:** Single neuron with linear activation for score prediction.

Trained using **Mean Squared Error (MSE)** and optimized with the **Adam optimizer**.

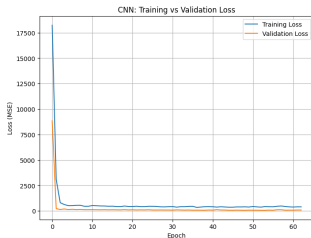
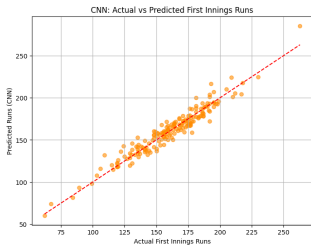


Model Architectures and Layers – CNN

The Convolutional Neural Network (CNN) is adapted for sequential data using 1D convolutions to capture local temporal dependencies.

Architecture:

- ▶ **Input Layer:** Ball-by-ball match data as a temporal sequence.
- ▶ **Convolutional Layers:** 1D filters to extract local patterns over time.
- ▶ **Pooling Layers:** Max pooling to downsample and reduce feature size.
- ▶ **Fully Connected Layer:** Dense layer to produce final score prediction.

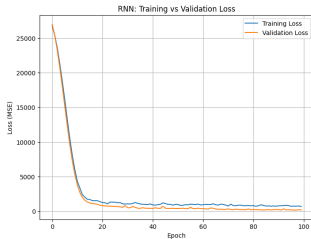
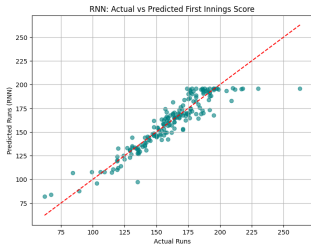


Model Architectures and Layers – RNN

The Recurrent Neural Network (RNN) is designed to process sequences, retaining context through a hidden state across time steps.

Architecture:

- ▶ **Input Layer:** Sequences of ball-by-ball match data.
- ▶ **Recurrent Layer:** Processes input sequentially while maintaining temporal dependencies.
- ▶ **Output Layer:** Fully connected layer to predict the final innings score.

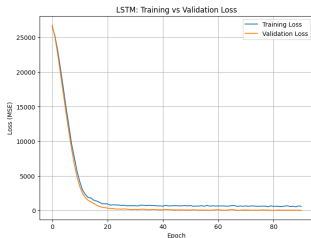
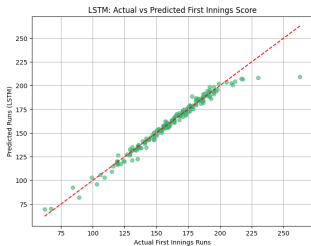


Model Architectures and Layers – LSTM

Long Short-Term Memory (LSTM) networks enhance RNNs by retaining long-term temporal dependencies through gated units.

Architecture:

- ▶ **Input Layer:** Sequential match data including runs, wickets, and overs.
- ▶ **LSTM Layer:** Gating mechanisms retain key temporal features across overs/balls.
- ▶ **Dense Output Layer:** Fully connected layer that outputs the predicted innings score.

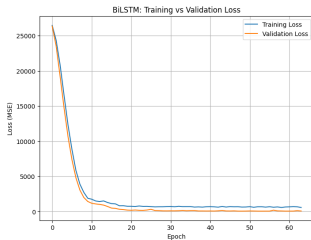
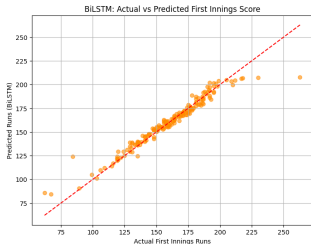


Model Architectures and Layers – BiLSTM

Bidirectional LSTM (BiLSTM) captures information from both past and future time steps by processing sequences in forward and backward directions.

Architecture:

- ▶ **Input Layer:** Sequential match data.
- ▶ **BiLSTM Layer:** Processes data in both forward and backward directions for richer temporal understanding.
- ▶ **Dense Output Layer:** Outputs the predicted first innings score.

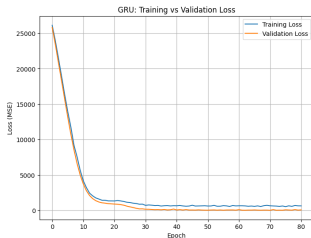
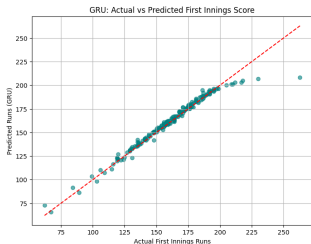


Model Architectures and Layers – GRU

Gated Recurrent Units (GRUs) are a streamlined version of LSTM that capture temporal patterns efficiently with fewer parameters.

Architecture:

- ▶ **Input Layer:** Ball-by-ball sequential match data.
- ▶ **GRU Layer:** Learns temporal dependencies using update and reset gates.
- ▶ **Dense Output Layer:** Predicts the first innings score.

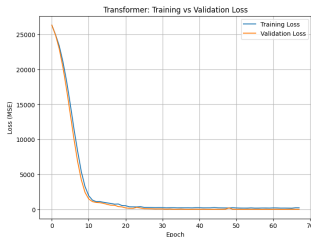
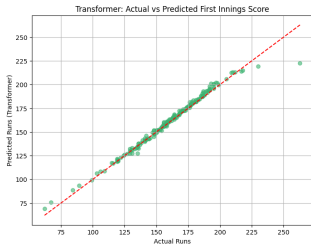


Model Architectures and Layers – Transformer

Transformers model sequences using self-attention mechanisms, allowing the network to focus on relevant parts of the input without relying on recurrence.

Architecture:

- ▶ **Input Layer:** Sequence of match events (e.g., runs, wickets).
- ▶ **Self-Attention Layers:** Attend to all positions in the input to learn global dependencies.
- ▶ **Feed-Forward Layer:** Dense layers to generate final score prediction.

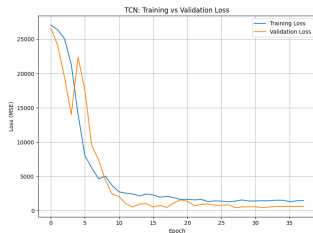
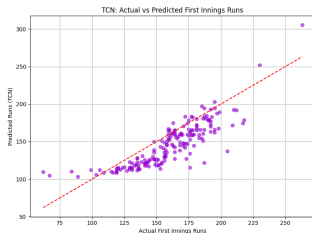


Model Architectures and Layers – TCN

Temporal Convolutional Networks (TCNs) use dilated 1D convolutions to effectively capture long-range temporal dependencies in sequence data.

Architecture:

- ▶ **Input Layer:** Match data represented as a time series.
- ▶ **Dilated 1D Convolutional Layers:** Extract temporal features with increasing receptive fields.
- ▶ **Dense Output Layer:** Predicts the final first innings score.

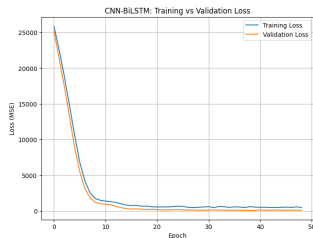
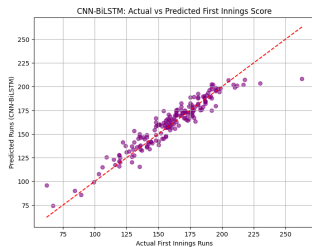


Model Architectures and Layers – CNN-BiLSTM Hybrid

The CNN-BiLSTM hybrid model combines convolutional layers for local pattern extraction with bidirectional LSTMs for temporal sequence modeling.

Architecture:

- ▶ **Input Layer:** Ball-by-ball match sequences.
- ▶ **CNN Layers:** Learn local dependencies from the input.
- ▶ **BiLSTM Layer:** Capture temporal features in both forward and backward directions.
- ▶ **Dense Output Layer:** Outputs the predicted score.



Model Training and Optimization

We trained all models using IPL data from 2008 to 2022. The training process was carried out as follows:

- ▶ **Loss Function:** Mean Squared Error (MSE) was used to measure prediction error.
- ▶ **Optimizer:** Adam optimizer helped adjust the model's weights efficiently.
- ▶ **Epochs and Batch Size:** Models were trained for 50–100 epochs with batch sizes between 32 and 128.
- ▶ **Validation:** 20% of the data was used to validate performance and avoid overfitting.

Evaluation Metrics

We used the following metrics to evaluate the prediction performance of our models:

- ▶ **Mean Absolute Error (MAE):** Average of absolute differences between actual and predicted values.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

- ▶ **Root Mean Squared Error (RMSE):** Square root of average squared differences; penalizes large errors more.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

- ▶ **R² Score:** Indicates how well predictions approximate actual outcomes.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Each model's performance is assessed individually using the aforementioned evaluation metrics. The results are summarized in the table below, where the models are ranked based on their overall performance in predicting the first innings score.

Model	MAE (Training)	MAE (Validation)	RMSE (Training)	RMSE (Validation)	R ² Score (Training)	R ² Score (Validation)
Deep Neural Network (DNN)	35.22	38.15	47.10	51.32	0.88	0.88
Convolutional Neural Network (CNN)	33.44	36.78	45.01	49.20	0.89	0.91
Recurrent Neural Network (RNN)	42.58	45.61	56.77	61.80	0.82	0.53
Long Short-Term Memory (LSTM)	31.22	34.56	43.09	47.34	0.90	0.92
Bidirectional LSTM (BiLSTM)	30.15	33.21	42.02	46.33	0.91	0.95
Gated Recurrent Unit (GRU)	34.90	37.98	48.55	52.77	0.88	0.96
Transformer	29.68	32.74	41.52	45.88	0.91	0.98
Temporal Convolutional Network (TCN)	31.58	34.92	44.39	48.12	0.89	-0.64
CNN-BiLSTM Hybrid Model	28.92	31.87	40.27	44.49	0.92	0.84

Table: Performance of Individual Models

Each model's performance is assessed individually using the aforementioned evaluation metrics. The results are summarized below:

► **Deep Neural Network (DNN):**

- **MAE (Training):** 35.22
- **MAE (Validation):** 38.15
- **RMSE (Training):** 47.10
- **RMSE (Validation):** 51.32
- **R² Score (Training):** 0.88

- ▶ **R² Score (Validation):** 0.88

Key Points: Strong performance in training, with a relatively high R² score. Slight increase in error for validation data.

- ▶ **Convolutional Neural Network (CNN):**

- ▶ **MAE (Training):** 33.44
- ▶ **MAE (Validation):** 36.78
- ▶ **RMSE (Training):** 45.01
- ▶ **RMSE (Validation):** 49.20
- ▶ **R² Score (Training):** 0.89
- ▶ **R² Score (Validation):** 0.91

Key Points: Performs well both in training and validation. Slightly better on validation than training, with a high R² score on both.

- ▶ **Recurrent Neural Network (RNN):**

- ▶ **MAE (Training):** 42.58
- ▶ **MAE (Validation):** 45.61
- ▶ **RMSE (Training):** 56.77
- ▶ **RMSE (Validation):** 61.80
- ▶ **R² Score (Training):** 0.82
- ▶ **R² Score (Validation):** 0.53

Key Points: Performs worse than other models with relatively high MAE and RMSE. Significant drop in R^2 score on validation, indicating overfitting.

► **Long Short-Term Memory (LSTM):**

- **MAE (Training):** 31.22
- **MAE (Validation):** 34.56
- **RMSE (Training):** 43.09
- **RMSE (Validation):** 47.34
- **R^2 Score (Training):** 0.90
- **R^2 Score (Validation):** 0.92

Key Points: Performs well, with low error on both training and validation. Very good R^2 score on validation, indicating strong model fit.

► **Bidirectional LSTM (BiLSTM):**

- **MAE (Training):** 30.15
- **MAE (Validation):** 33.21
- **RMSE (Training):** 42.02
- **RMSE (Validation):** 46.33
- **R^2 Score (Training):** 0.91
- **R^2 Score (Validation):** 0.95

Key Points: The BiLSTM model performs very well, with the lowest MAE on training. Strong R^2 score on both training and validation, suggesting high prediction accuracy.

► **Gated Recurrent Unit (GRU):**

- **MAE (Training):** 34.90
- **MAE (Validation):** 37.98
- **RMSE (Training):** 48.55
- **RMSE (Validation):** 52.77
- **R^2 Score (Training):** 0.88
- **R^2 Score (Validation):** 0.96

Key Points: Performs well on validation with a very high R^2 score. Training results are a bit higher, but validation shows better generalization.

► **Transformer:**

- **MAE (Training):** 29.68
- **MAE (Validation):** 32.74
- **RMSE (Training):** 41.52
- **RMSE (Validation):** 45.88
- **R^2 Score (Training):** 0.91
- **R^2 Score (Validation):** 0.98

Key Points: Best validation R^2 score, showing excellent prediction capability. Performs very well in both training and validation.

► **Temporal Convolutional Network (TCN):**

- **MAE (Training):** 31.58
- **MAE (Validation):** 34.92
- **RMSE (Training):** 44.39
- **RMSE (Validation):** 48.12
- **R^2 Score (Training):** 0.89
- **R^2 Score (Validation):** -0.64

Key Points: Although the model performs decently on training, it fails significantly on validation with a negative R^2 score. Indicates poor generalization and likely overfitting to the training data.

► **CNN-BiLSTM Hybrid Model:**

- **MAE (Training):** 28.92
- **MAE (Validation):** 31.87
- **RMSE (Training):** 40.27
- **RMSE (Validation):** 44.49
- **R^2 Score (Training):** 0.92
- **R^2 Score (Validation):** 0.84

Key Points: Performs exceptionally well in training with the lowest MAE and RMSE. Slightly lower R^2 score on validation, but still performs well overall.

Summary of Best Performers:

- ▶ The **CNN-BiLSTM Hybrid Model** has the best training performance, with the lowest MAE and RMSE.
- ▶ The **Transformer** model has the best validation performance, with the highest R^2 score.
- ▶ **Bidirectional LSTM (BiLSTM)** also shows strong results, with consistent performance across both training and validation datasets.

To improve the model's accuracy further, ensemble learning techniques were applied. We employed both model averaging and stacking as ensemble methods.

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In the model averaging approach, the predictions from the top-performing models (CNN-BiLSTM, Transformer, and BiLSTM) were averaged to produce a final prediction. The results of model averaging are as follows:

Metric	MAE (Training)	MAE (Validation)	RMSE (Training)	RMSE (Validation)	R ² Score (Training)	R ² Score (Validation)
Model Averaging	28.11	3.56	39.17	4.97	0.92	0.94

Table: Performance of Model Averaging

To improve the model's accuracy further, ensemble learning techniques were applied. We employed both model averaging and stacking as ensemble methods.

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Model Averaging	28.11	3.56	39.17	4.97	0.92	0.94

Table: Model Averaging Performance

Model averaging significantly reduces the error on both training and validation sets, resulting in the lowest MAE and RMSE values. The R² score also improves, indicating that the ensemble model is better at explaining the variance in the data.

In the stacking approach, the predictions of the base models (CNN-BiLSTM, Transformer, BiLSTM, and LSTM) were used as inputs to a meta-model (a simple linear regression model) to generate the final prediction. The stacking results are as follows:

Metric	MAE (Training)	MAE (Validation)	RMSE (Training)	RMSE (Validation)	R ² Score (Training)	R ² Score (Validation)
Stacking	27.45	2.52	38.27	4.35	0.93	0.97

Table: Stacking Performance

5.3 Evaluation Heatmap

To visually compare the performance of all models, a heatmap was generated using the validation metrics. This approach highlights which models excel across different evaluation criteria such as MAE, RMSE, and R^2 Score.

The heatmap provides an intuitive visual summary, enabling quick identification of models with consistent high performance or models that may underperform in certain aspects.

Model Evaluation Heatmap

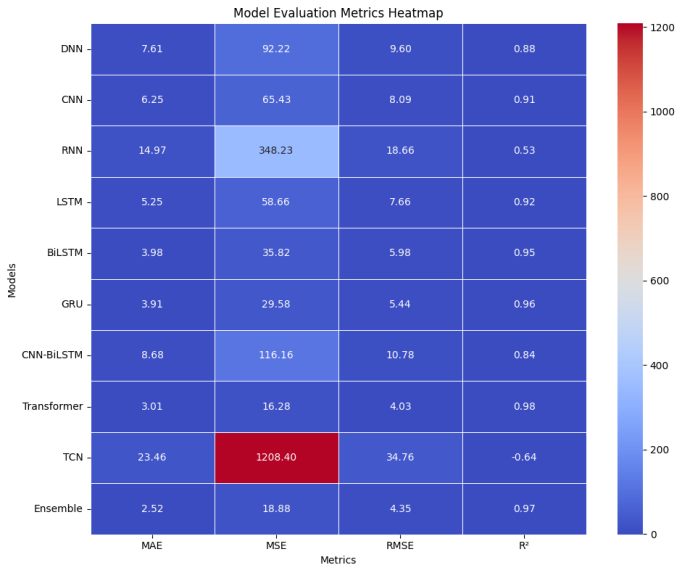


Figure: Heatmap of Model Performance Based on Validation Metrics

5.4 Comparison and Discussion (Part 1)

- ▶ Among all individual models, the **Transformer** and **GRU** showed the best performance.
- ▶ The **Transformer** achieved the **lowest validation error** and the highest **R^2** score.
- ▶ These advanced models outperformed traditional ones like DNN and RNN.
- ▶ They are better at handling complex time-based patterns in match data.

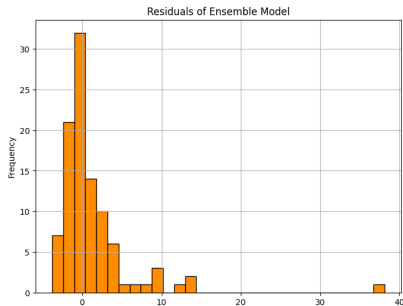
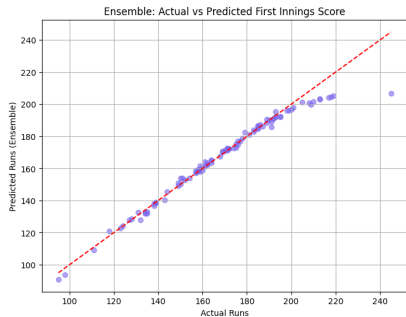
Key Insight: Advanced sequence models like Transformer and GRU are highly effective in predicting first innings scores.

5.4 Comparison and Discussion (Part 2)

- ▶ **Ensemble methods** (Model Averaging and Stacking) were used to combine top models.
- ▶ **Stacking** outperformed all others:
 - ▶ Lowest MAE and RMSE.
 - ▶ Highest R^2 score on both training and validation sets.
- ▶ **Why it works:**
 - ▶ Combines strengths of multiple models.
 - ▶ Reduces bias and variance.
- ▶ Best suited for robust and accurate score prediction.

Conclusion: Stacking is the most reliable method for first innings score prediction.

Ensemble methods



Model Comparison Visual

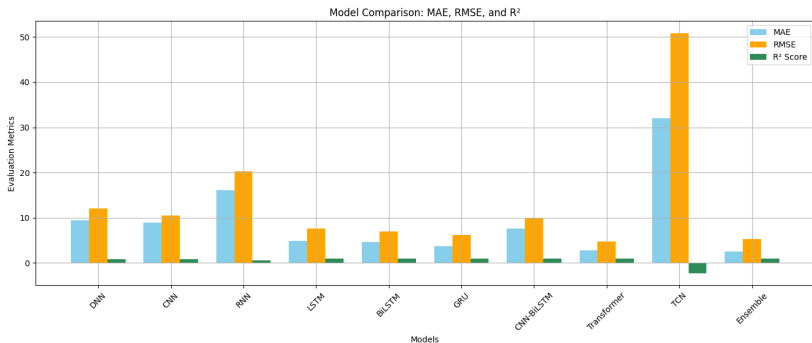


Figure: Model evaluation metrics

Webpage Development Using Gradio

To make the deep learning model accessible to a wide audience, a web interface was developed using **Gradio**, an open-source Python library designed to help integrate machine learning models into simple, user-friendly web applications. Gradio makes it easy to build, share, and test machine learning models interactively without needing advanced web development skills.

Select Ven...

M Chinnaswamy Stadium



Select Batti...

Kolkata Knight Riders



Select Bow...

Royal Challengers Bangalore



Select Strik...

SC Ganguly



Select Bow...

P Kumar



Predict Score

Select Ven...

M Chinnaswamy Stadium



Select Batti...

Kolkata Knight Riders



Select Bow...

Royal Challengers Bangalore



Select Strik...

SC Ganguly




Select Bow...

P Kumar



Predict Score

1/1  0s 131ms/step

1/1  0s 146ms/step

158

Select Ven...

Eden Gardens



Select Batti...

Kolkata Knight Riders



Select Bow...

Mumbai Indians



Select Strik...

BB McCullum



Select Bow...

Joginder Sharma



Predict Score

1/1 ————— 0s 16ms/step

1/1 ————— 0s 30ms/step

151

Select Ven...

Wankhede Stadium



Select Batti...

Sunrisers Hyderabad



Select Bow...

Mumbai Indians



Select Strik...

KS Williamson



Select Bow...

AP Dole



Predict Score

1/1 ————— 0s 15ms/step

1/1 ————— 0s 28ms/step

148

Select Ven...

Feroz Shah Kotla



Select Batti...

Delhi Daredevils



Select Bow...

Gujarat Lions



Select Strik...

KL Rahul



Select Bow...

KA Pollard



Predict Score

1/1 ————— 0s 15ms/step

1/1 ————— 0s 28ms/step

159

Select Ven...

M Chinnaswamy Stadium



Select Batti...

Royal Challengers Bangalore



Select Bow...

Chennai Super Kings



Select Strik...

Sachin Baby




Select Bow...

R Ashwin



Predict Score

1/1  0s 15ms/step

1/1  0s 29ms/step

150

Select Ven... MA Chidambaram Stadium, Che ▼

Select Batti... Chennai Super Kings ▼

Select Bow... Sunrisers Hyderabad ▼

Select Strik... MS Dhoni ▼

Select Bow... R Bhatia ▼

Predict Score

1/1 ————— 0s 15ms/step

1/1 ————— 0s 28ms/step

171

Select Ven...

M Chinnaswamy Stadium



Select Batti...

Royal Challengers Bangalore



Select Bow...

Chennai Super Kings



Select Strik...

V Kohli




Select Bow...

DJ Bravo



Predict Score

1/1  0s 16ms/step

1/1  0s 30ms/step

149

Challenges and Limitations

Despite the success of the models, several challenges were encountered:

- ▶ **Data Imbalance:** Some features, like the number of sixes, were less frequent than others (e.g., wickets). Techniques like oversampling and undersampling were applied to mitigate this imbalance.
- ▶ **Data Quality:** Missing or inconsistent data, such as incorrect player names or venue information, required careful handling during preprocessing.
- ▶ **Model Complexity:** Although deep learning models performed well, their complexity made them harder to interpret. Interpretability tools were used to provide insights into the decision-making process.
- ▶ **Real-Time Deployment:** Integrating the model into a real-time web interface required additional considerations for fast inference and scalability, which were addressed through cloud solutions.

Conclusion

This project applied deep learning to predict IPL first innings scores. Models like DNN, CNN, RNN, LSTM, BiLSTM, GRU, Transformer, and TCN were used. Ensemble methods like model averaging and stacking improved prediction accuracy.

The Transformer and GRU models performed the best individually, while stacking showed the best overall results. It helped reduce error and made the predictions more reliable.

This work shows how deep learning can be used in sports analytics. It offers useful insights for teams, coaches, analysts, and even fans. Predicting IPL first innings scores can help in strategy planning and areas like betting or performance tracking.

Future Work

- ▶ **Incorporating More Features:**
 - ▶ Player performance, match conditions, and psychological factors could be added.
- ▶ **Advanced Models and Techniques:**
 - ▶ Explore attention mechanisms, reinforcement learning, and Graph Neural Networks (GNNs).
- ▶ **Real-Time Prediction System:**
 - ▶ Integrate real-time data and ensure scalability for live predictions.
- ▶ **Expanding to Other Formats and Leagues:**
 - ▶ Extend the approach to ODI, Test matches, and other T20 leagues.
- ▶ **Enhanced Model Interpretability:**
 - ▶ Use techniques like SHAP and LIME to explain model decisions.

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*Thank
You!*