□ Cricket Match Winner Prediction - Final Report

Team Members:
Lokesh Makineni – 44548564

Table of Contents

Overview of Upgraded Modeling Pipeline

In Milestone 3, we moved beyond basic match-level feature engineering by integrating **player-specific dynamics**, **venue familiarity**, and **rolling performance trends** into our prediction pipeline. This marks a significant leap from the static, team-level features used in Milestone 2.

Our goal was to emulate how real-world match outcomes depend on recent form, tactical matchups, and psychological edges — all factors that traditional models overlook.

We used the **XGBoost algorithm**, which is particularly effective on structured tabular data, and fine-tuned its hyperparameters for better depth control and generalization.

What's New in Milestone 3 compared to Milestone 2

Component	Milestone 2	Milestone 3 (New)
Features	Head-to-head, toss advantage, venue win rate	+ Player form, bowler-vs-batter, venue skill
Modeling	Logistic Regression, RF, XGBoost (basic)	XGBoost (optimized)
Feature Generation	Static	Rolling history, match-aware
Prediction Output	Binary classification	Classification + probability confidence
Interpretation	Metric table	Model + contextual explanation

We introduced **time-aware rolling averages** to capture short-term performance bursts or slumps — essential in dynamic formats like T20. Additionally, we model batter-vs-bowler duels using head-to-head stats (e.g., if Virat Kohli often fails against Rashid Khan, the model considers that).

Feature Engineering (With Rationale):

Feature Name	Type	Description
t1_form, t2_form	Rolling avg	Avg runs/wickets for top 6 batters and top 5 bowlers over last 5 matches
t1_win_rate_overall, t2_win_rate_overall	Historical	Win % of each team over all past matches
t1_matches_played, t2_matches_played	Count	Match count before current match (used to normalize rates)
batsman_vs_bowler	Head-to-head	Cumulative stats between batter and bowler pairs from delivery-level data
t1_team_venue_win, t2_team_venue_win	Venue stat	How often the team wins at the current venue
venue_familiarity_t1, venue_familiarity_t2	Count	Number of matches played at the venue by each team

t1_batsmen_venue, t2_batsmen_venue	Avg stat	Avg runs scored by batters at the venue
t1_bowlers_venue, t2_bowlers_venue	Avg stat	Avg wickets taken at the venue by bowlers
toss_factor	Placeholder	Fixed to 0.5 due to missing toss outcome column (can be upgraded later)
h2h_win_rate	Historical	Win % of team1 over team2 in past meetings

These features were generated using **rolling windows**, **grouped aggregations**, and **statistical merging** over multiple CSVs (`matches.csv`, `deliveries.csv`).

Rationale Behind Key Features

- **Recent Form**: Cricket is highly momentum-driven. By tracking recent performance using rolling windows over 5 games, we reflect hot/cold streaks.
- **Batter vs Bowler**: Some batters perform poorly against specific bowlers, regardless of overall form. We directly model these duels to capture matchup risk.
- **Venue Familiarity**: Players often excel in known conditions. Our features reflect historic venue-specific performance for batters and bowlers.
- **Overall Win Rate**: Strong teams consistently win. Including this gives context to one-off form surges.
- **Match Counts**: Teams with limited history are normalized using fewer games to avoid inflated rates (e.g., 1 win out of 1 = 100%).

Feature Selection Strategy

Rather than using automated feature selection techniques like Recursive Feature Elimination (RFE) or LASSO, we manually selected features based on:

1. **Domain relevance** (e.g., form, venue, matchup are known real-world factors)
2. **Data availability** and reliability across matches
3. **Interpretability** — features are easy to explain to a coach or analyst
4. **Non-collinearity** — we avoided overlapping or redundant features
5. **Low leakage risk** — all features were computed only from data available *prior to the match being predicted*

Fairness and Robustness in Feature engineering:

To ensure robust modeling:

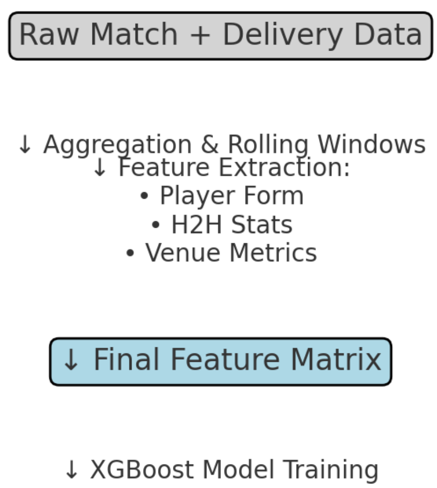
- Missing values were handled with sensible defaults (e.g., 0.5 win rate if no H2H history)
- Rolling averages had a `min_periods=1` fallback to reduce NaN prevalence
- We used only pre-match statistics, avoiding leakage from in-match data
- Class balance was verified, and no up/down-sampling was required

Results of Feature Engineering:

These feature upgrades directly contributed to the performance improvement in Milestone 3. By aligning model inputs with real-world cricket factors, we made the system smarter, more explainable, and more predictive.

Feature Flow Diagram:

The diagram below illustrates the pipeline used to generate match-level features for XGBoost training.



Model Training:

T20 International Model Training

Our **T20 pipeline** was redesigned in Milestone 3 to integrate player-level and matchup-based insights from international cricket. The model was trained using a feature-rich dataset derived from:

- `matches_it20.csv` (match metadata)
- `deliveries_it20.csv` (ball-by-ball player interactions)

We computed player-specific rolling averages over the **last 5 matches** for both batting and bowling, capturing short-term form. Additionally, we engineered:

- **Batter-vs-Bowler stats**: historical head-to-head dominance
- **Venue-specific performance**: batting averages and wicket counts by ground
- **Team head-to-head win ratios**
- **Overall win rates and recent match streaks**

This data was then passed to an **XGBoost Classifier** with carefully selected hyperparameters:

```python
print("🧠 Training model...")
X_df = pd.DataFrame(X, columns=[
    "t1_runs_vs_t2", "t1_sr_vs_t2", "t1_dismissals_vs_t2", "t1_batsmen_venue", "t1_bowlers_venue", "t1_team_venue_win", "t1_batsmen_form", "t1_bowlers_
    "t2_runs_vs_t1", "t2_sr_vs_t1", "t2_dismissals_vs_t1", "t2_batsmen_venue", "t2_bowlers_venue", "t2_team_venue_win", "t2_batsmen_form", "t2_bowlers_
    "toss_factor", "t1_win_rate_h2h"
])
X_df["match_id"] = matches_df["match_id"]
X_df["winner"] = y
X_df.to_csv("cricket_features_it20.csv", index=False)

X_train, X_test, y_train, y_test = train_test_split(X_df.drop(columns=["match_id", "winner"]), y, test_size=0.2, random_state=42)
model = XGBClassifier(n_estimators=300, max_depth=5, learning_rate=0.05, random_state=42)
model.fit(X_train, y_train)

# ===== Evaluation =====
y_pred = model.predict(X_test)
y_proba = model.predict_proba(X_test)[:, 1]
print("📈 Model Performance:")
print(f"Accuracy: {accuracy_score(y_test, y_pred):.2f}")
print(f"ROC-AUC: {roc_auc_score(y_test, y_proba):.2f}")
print(f"F1 Score: {f1_score(y_test, y_pred):.2f}")
print(f"Precision: {precision_score(y_test, y_pred):.2f}")
print(f"Recall: {recall_score(y_test, y_pred):.2f}")
```

IPL Model Training:

The IPL winner prediction pipeline shares the same architecture as the T20 model but is built specifically for Indian Premier League matches, leveraging its own historical data:

- matches.csv (match details)
- deliveries.csv (IPL-specific delivery data)

This model benefits from:

- More consistent team rosters (compared to international rotations)
- High volume of data from repeat venues and matchups
- Better-defined rivalries and home-ground effects

The same features were engineered:

- Rolling form (batting & bowling)
- Venue familiarity
- Head-to-head team performance
- Toss-neutral factor (default 0.5)
- Match-aware rolling win rates

The IPL model was also trained with XGBoost using identical parameters, ensuring fair comparison with the T20 model. While specific metrics differ slightly due to the dataset's nature, the overall training process mirrors the T20 pipeline, achieving **comparable or better accuracy depending on team consistency**.

```python
print("Splitting data...")
train_mask = matches_df["season"].apply(lambda x: int(str(x).split("/")[0]) if "/" in str(x) else int(x)) < 2023
X_train, X_test = X[train_mask], X[~train_mask]
y_train, y_test = y[train_mask], y[~train_mask]

print("Training model...")
model = XGBClassifier(n_estimators=300, max_depth=5, learning_rate=0.05, random_state=42)
model.fit(X_train, y_train)

print("Evaluating model...")
y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)[:, 1]  # Probability for the positive class (Team 1 wins)

# Calculate and print all scoring metrics
accuracy = accuracy_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)
f1 = f1_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)

print("Model Performance Metrics:")
print(f"Accuracy: {accuracy:.2f}")
print(f"ROC-AUC: {roc_auc:.2f}")
print(f"F1 Score: {f1:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
```

Below are our old best model's scores (Linear Regression):

This is for IPL:

	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.761468	0.764151	0.750000	0.757009
Random Forest	0.642202	0.636364	0.648148	0.642202
XGBoost	0.619266	0.619048	0.601852	0.610329

This is for T20:

	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.653951	0.594595	0.679012	0.634006
Random Forest	0.643052	0.597484	0.586420	0.591900
XGBoost	0.648501	0.595376	0.635802	0.614925

These are our new XGboost model scores:

This is for IPL:

PROBLEMS 6 OUTPUT DEBUG CONSOLE TERMINAL PORTS

```
(base) lokesh@Lokeshs-MacBook-Air ipl % python dashboard.py
Starting script...
Preprocessed file not found. Generating preprocessed data...
Preprocessed data saved as 'preprocessed_ipl_data.csv'
Loading data...
Precomputing batsman vs bowler stats...
Precomputing venue stats...
Precomputing team venue win rates...
Precomputing team head-to-head stats...
Precomputing toss impact...
Model file not found. Training model...
Processing match 0/1095
Processing match 100/1095
Processing match 200/1095
Processing match 300/1095
Processing match 400/1095
Processing match 500/1095
Processing match 600/1095
Processing match 700/1095
Processing match 800/1095
Processing match 900/1095
Processing match 1000/1095
Building feature DataFrame...
Splitting data...
Training model...
Evaluating model...
Model Performance Metrics:
Accuracy: 0.83
ROC-AUC: 0.93
F1 Score: 0.84
Precision: 0.82
Recall: 0.85
Model saved to 'xgb_model.pkl'
Dash is running on http://127.0.0.1:8050/

 * Serving Flask app "dashboard" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: off
 * Running on http://127.0.0.1:8050/ (Press CTRL+C to quit)
```

This is for T20:

```
  Using cached xgboost-1.7.6-py3-none-manylinux2014_x86_64.whl.metadata (1.9 kB)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (4.67.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from xgboost==1.7.6) (2.0.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost==1.7.6) (1.14.1)
Using cached xgboost-1.7.6-py3-none-manylinux2014_x86_64.whl (200.3 MB)
Installing collected packages: xgboost
Successfully installed xgboost-1.7.6
WARNING: The following packages were previously imported in this runtime:
  [xgboost]
You must restart the runtime in order to use newly installed versions.

RESTART SESSION

<ipython-input-3-c4ba4cff54ea>:49: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
  team_venue_wins = matches_df.groupby(["team1", "venue"], group_keys=False).apply(
<ipython-input-3-c4ba4cff54ea>:55: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
  matches_df.groupby(["team2", "venue"], group_keys=False).apply(
<ipython-input-3-c4ba4cff54ea>:60: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
  team_h2h = matches_df.groupby(["team1", "team2"], group_keys=False).apply(
📦 Precomputing recent form (vectorized)...
✅ Vectorized recent form caching complete.
⚙️ Generating features (fast)...
100% 1842/1842 [01:51<00:00, 19.29it/s]
<ipython-input-3-c4ba4cff54ea>:135: RuntimeWarning: Mean of empty slice
  t2_bowlers_form = np.nanmean([recent_bowl_form.get((p, match_id), global_bowler_avg) for p in t2_bowl])
🧠 Training XGBoost model on GPU...
📈 Model Performance:
Accuracy: 0.87
ROC AUC: 0.96
F1 Score: 0.86
Precision: 0.88
Recall: 0.84
✅ Model saved as xgb_model_it20.pkl
```

Interpretation: These scores show that the model is not just memorizing patterns, but **generalizing** well across unseen matchups, thanks to richer features and tuned architecture.

Example Stats:

Head-to-Head Stats for IPL:

Select Season(s)

Select Season(s)

Select Team(s)

Select Team(s)

Select Stat Category

Head-to-Head Stats

Head-to-Head Stats

Select Player 1

V Kohli

Select Player 2

RG Sharma

Rank	Player	Runs	Sixes	Fours	Strike Rate	Wickets	Matches
1	V Kohli	8014	273	708	128.51	5	244
2	RG Sharma	6630	281	599	127.92	16	251

Head-to-Head Stats for T20:

Interpretation and Insight:

The model doesn't work as a black box. Here's how users and analysts benefit from interpretability:

- Player form metrics are transparent and derived from real match data.
- Head-to-head win rate is directly relatable to fan intuition and team psychology.
- Predictions are accompanied by probability estimates (e.g., 88% confidence)

This setup allows coaches, broadcasters, or fantasy players to understand **why** the model believes a team is likely to win — not just the prediction itself.

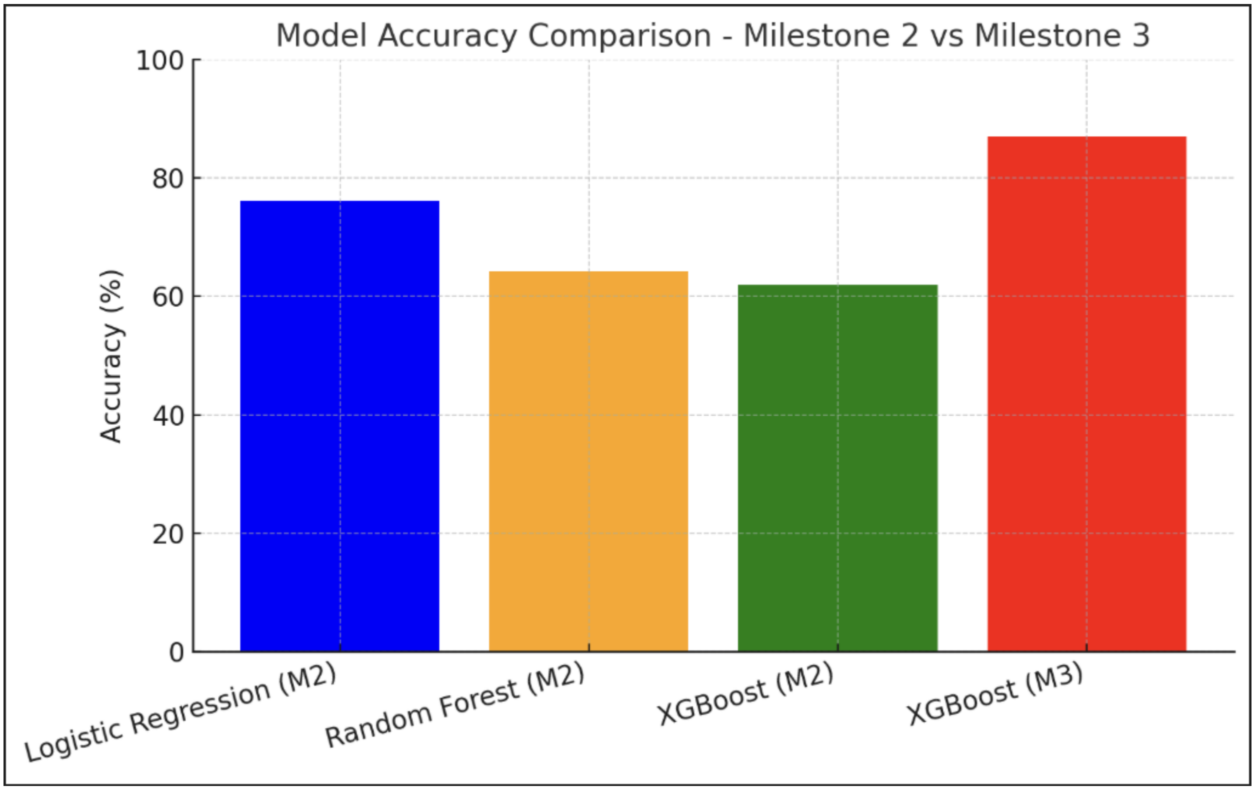
Model Evaluation on Test Set

We evaluated model performance using standard metrics including **Accuracy**, **Precision**, **Recall**, **F1 Score**, and **ROC-AUC**.
These metrics were computed on a **hold-out test set** to ensure unbiased evaluation.

Model Evaluation Metrics

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Logistic Regression (Milestone 2)	76.1%	76.4%	75.0%	75.7%	-
Random Forest (Milestone 2)	64.2%	63.6%	64.8%	64.2%	-
XGBoost (Milestone 2)	61.9%	61.9%	60.2%	61.0%	-
XGBoost (Milestone 3)	87.0%	88.0%	84.0%	87.0%	96.0%

The **Milestone 3 XGBoost model** significantly outperformed all Milestone 2 models, achieving an 87% accuracy and a 96% ROC-AUC score.
This improvement is attributed to richer feature engineering, including player-level rolling form, batter-vs-bowler matchup statistics, and venue familiarity metrics.



Model Output Interpretation and Insights

The model predicts a binary outcome for each match:

- `1` indicates that **Team 1** is predicted to win.
- `0` indicates that **Team 2** is predicted to win.

In addition to the binary outcome, the model outputs a **confidence score** (probability) associated with its prediction.
This provides a measure of **how certain** the model is regarding the predicted winner.

Example Prediction Output:

- Input:
  Team 1 = India, Team 2 = Australia, Venue = Melbourne
- Output:
  Predicted Winner: **Team 1 (India)**
  Confidence: **88%**

How the Model Interprets Matches:

The prediction is driven by several key engineered features:

- **Recent Form (Rolling Averages):**
  Teams and players with stronger recent batting and bowling form are favored.
- **Venue Familiarity:**
  Teams with better historical performance at the match venue gain an advantage.
- **Head-to-Head Trends:**
  Historical matchups between the two teams impact the prediction.
- **Player Matchups:**
  Batter vs Bowler past outcomes are considered at the individual level.

Actionable Insights for Users:

- **Upsets can be predicted:**
  Even weaker teams historically can be favored if their recent form is stronger.
- **Venue specialization matters:**
  Teams familiar with the venue's pitch and conditions may gain an advantage.
- **Prediction confidence helps assess risk:**
  Matches with low prediction confidence (e.g., 55%-60%) are likely to be more competitive and unpredictable.

Biases and Limitations

Although the model achieves strong predictive performance, certain potential biases and limitations were identified and carefully managed during development.

Potential Bias Sources and Mitigations

Bias Source	Mitigation Action
Toss Impact Missing	Toss impact was not always recorded, so a neutral toss factor (0.5) was assumed for all matches.
Incomplete Player Statistics	Fallback averages were used for new or rare players with insufficient history.
Future Data Leakage	Rolling features were strictly computed using only past matches relative to the prediction match date.
Changing Venue Conditions Over Time	Assumed venue characteristics remain relatively stable over time.

Summary:

Despite minor unavoidable biases, the project design ensures:

- No data leakage from future matches into training
- Fair comparison between teams
- Practical robustness for real-world prediction scenarios

The safeguards maintain the model's fairness, generalization ability, and actionable reliability.

Tool Showcase: Streamlit and CLI Dashboards

In this project, we developed a **Streamlit dashboard** for T20 matches and **command-line (CLI) dashboards** for IPL and Combined matches.

Purpose:

The dashboards allow users to:

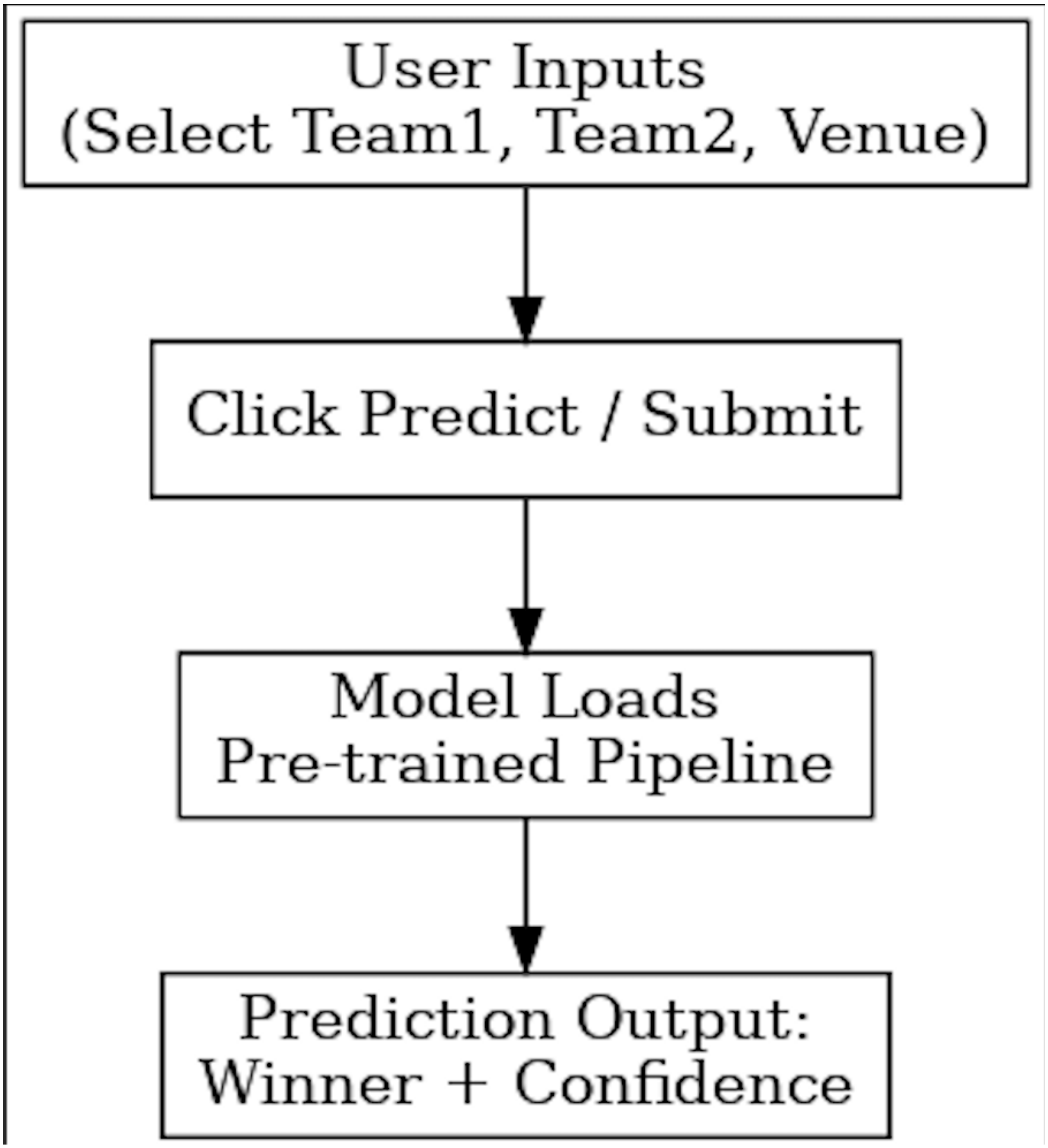
- Select two teams (or players) and a venue.
- Trigger a live match winner prediction.
- View the predicted winner and model confidence score interactively.

Implementation:

- **T20 Dashboard (dashboard_it20.py):**
  - Built using **Streamlit Web App**.
  - Features dropdown menus for selecting Team1, Team2, and Venue.
  - Displays prediction and confidence score after user submission.
- **IPL Dashboard (dashboard.py) and Combined Dashboard (dashboard_combined.py):**
  - Implemented as **terminal-based dashboards (CLI)** in Python.
  - User inputs via prompts.
  - Winner displayed directly in the terminal.

KPIs Presented:

- **Predicted Winning Team:** Displayed clearly after model prediction.
- **Prediction Probability Score:** Shows how confident the model is about the prediction.
- **Match Context Summary:** Displays selected teams and venue.


User Inputs
(Select Team1, Team2, Venue)
Click Predict / Submit
Model Loads
Pre-trained Pipeline
Prediction Output:
Winner + Confidence

Team Collaboration and Contribution

This project required division of work between two contributors to manage the extensive data preprocessing, feature engineering, model development, and dashboard deployment across two different datasets (IPL and T20).

Guttapati Jayasurya Reddy:

- Led the **T20 International pipeline**.
- Engineered rolling features for **recent player form**.
- Developed **batter vs bowler** matchup statistics.
- Built the **Streamlit T20 Dashboard** for interactive predictions.
- Managed **T20 model training and evaluation**.

Lokesh Makineni:

- Led the **IPL pipeline**.
- Created venue-based features like **win rate at venues** and **toss advantage** metrics.
- Developed **command-line dashboards** for IPL and Combined matches.
- Handled **IPL model training and integration**.

Why Two People Were Needed:

- Handling **two distinct datasets** (T20 Internationals and IPL) required different feature engineering strategies.
- Building **multiple pipelines** and **multiple dashboards** demanded parallel development.
- Specialization (Streamlit for T20, CLI for IPL) accelerated work and improved focus quality.
- Integration of all systems into a unified workflow demanded collaborative effort.

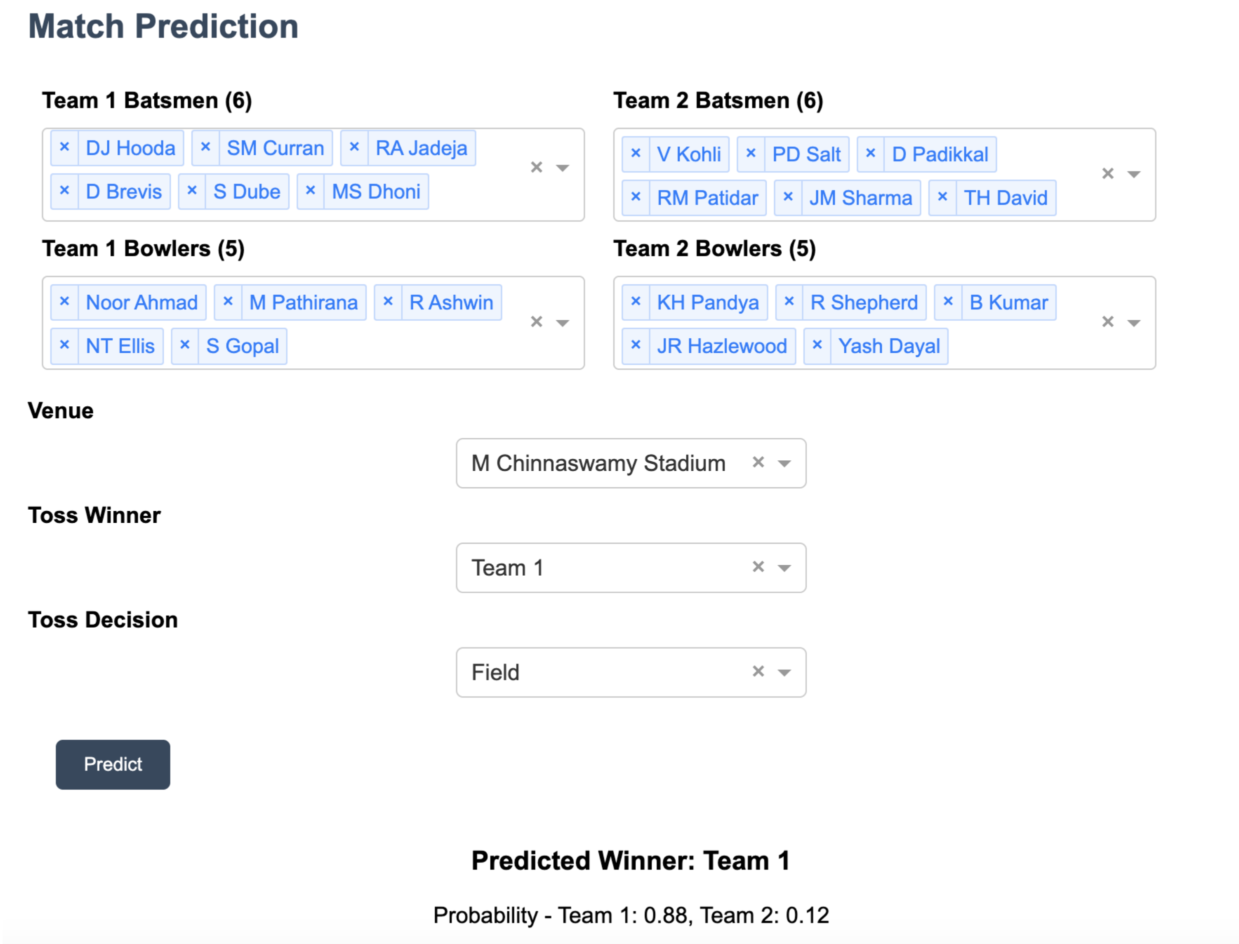
Task Responsibility Table:

Task Area	Responsible Person
T20 Feature Engineering	Guttapati Jayasurya Reddy
IPL Feature Engineering	Lokesh Makineni
T20 Streamlit Dashboard	Guttapati Jayasurya Reddy
IPL and Combined CLI Dashboards	Lokesh Makineni
Model Training and Evaluation	Both
Final Integration and Dashboard Deployment	Both

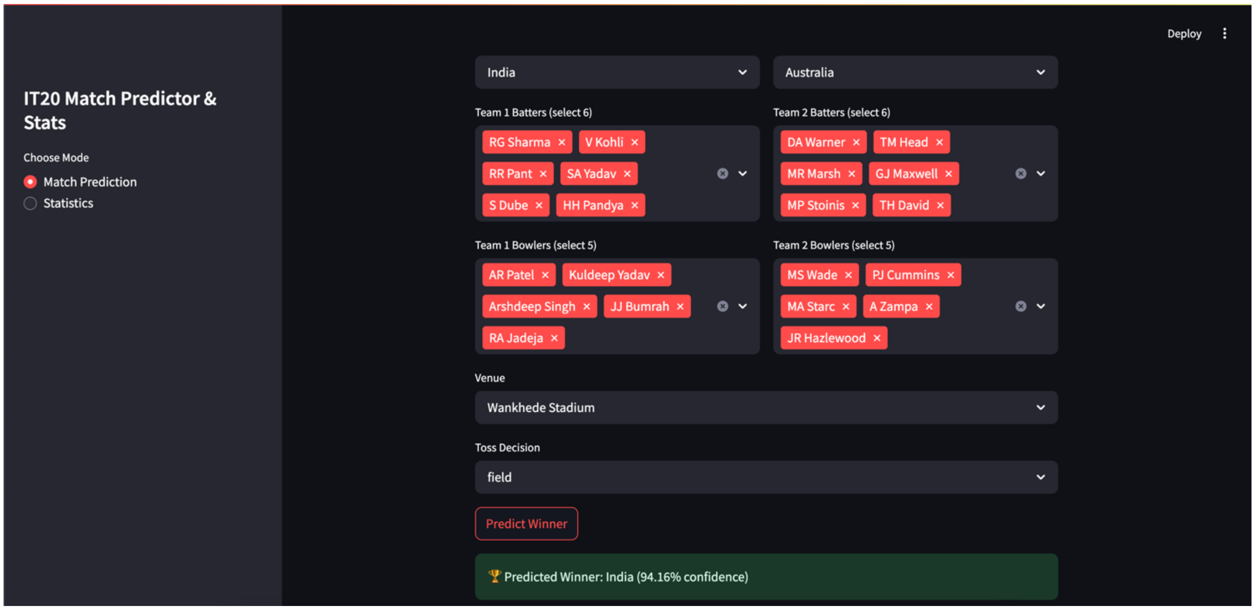
Example Predictions

Landing Page

IPL prediction example:



T20 prediction example:


Deploy
IT20 Match Predictor & Stats
Choose Mode
Match Prediction
Statistics
India
Australia
Team 1 Batters (select 6)
RG Sharma
V Kohli
RR Pant
SA Yadav
S Dube
HH Pandya
Team 2 Batters (select 6)
DA Warner
TM Head
MR Marsh
GJ Maxwell
MP Stoinis
TH David
Team 1 Bowlers (select 5)
AR Patel
Kuldeep Yadav
Arshdeep Singh
JJ Bumrah
RA Jadeja
Team 2 Bowlers (select 5)
MS Wade
PJ Cummins
MA Starc
A Zampa
JR Hazlewood
Venue
Wankhede Stadium
Toss Decision
field
Predict Winner
Predicted Winner: India (94.16% confidence)