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IPL Score Prediction using Deep Learning Learning

Dr. A. J. Kadam[1], Ms. Bahikar Vaishnavi[2]

[1]Lecturer, Department of Computer Engineering, AISSMS COE ,Pune, Maharashtra, India
[2,]Student, Department of Artificial Intelligence & Data Science, AISSMS COE ,Pune, Maharashtra, India

ABSTRACT:

Cricket is one of the most popular sports in the world, with the Indian Premier League (IPL) attracting a massive global audience. Predicting the outcome of cricket matches or scores has long intrigued analysts and enthusiasts alike due to the sport's dynamic and uncertain nature. With the advent of deep learning and advanced data analytics, it is now possible to build models that can capture the complex patterns in cricket data to make accurate predictions. This project focuses on developing a deep learning-based application to predict the final score of an IPL match using historical and live match data. By employing a custom neural network architecture trained on features such as runs, wickets, overs, player performance, and team statistics, the model aims to forecast the projected score with a high degree of accuracy. This research not only showcases the power of deep learning in sports analytics but also paves the way for more intelligent decision-support systems for teams, broadcasters, and fans.

Keywords: IPL, score prediction, deep learning, sports analytics, neural networks, cricket data, machine learning, match forecasting.

INTRODUCTION:

People are increasingly interested in predicting the outcome of sports events like the Indian Premier League (IPL), given the dynamic nature of cricket. Accurate score prediction can provide valuable insights for teams, analysts, and fans. Traditional methods of forecasting scores often rely on historical data and expert analysis, but deep learning techniques have shown great promise in improving the accuracy of such predictions. This project aims to develop a custom deep learning model to predict the score of IPL matches using features such as player statistics, team performance, historical match data, and live game metrics. The model is built using a custom Convolutional Neural Network (CNN) architecture with multiple layers to process and learn patterns from the data. The CNN consists of convolutional layers, max-pooling layers, dense layers, and a final output layer that predicts the IPL match score. The dataset used for training the model includes comprehensive information on past IPL seasons, player performances, and match statistics. By leveraging the power of deep learning, this model provides a more accurate and efficient way to predict IPL scores, which can be used for real-time forecasting and analysis during ongoing matches.

LITERATURESURVEY:

The model identifies American Sign Language using deep learning and computer vision [1]. The model gathers temporal and spatial attributes from video segments. Subsequently, to detect spatial attributes, we use Inception, a Convolutional Neural Network (CNN). Subsequently, to model temporal properties, we use a recurrent neural network (RNN). This research used an American Sign Language dataset.

A deep learning-based method for recognizing static sign language signals [2]. Humans can communicate proficiently using sign language, and significant research in computer vision is now under progress. The first research on Indian Sign Language (ISL) identification concentrated on the detection of significant, distinct hand signals; hence, only a limited number of ISL signs were selected for recognition. A cumulative collection of 35,000 signed photographs of over 100 static signs has been amassed from diverse users. The proposed system's efficacy is evaluated on around 50 CNN models.

Utilization of deep convolutional neural networks for the recognition of sign language [3]. This research utilizes a capture approach including continuous sign language video in selfie mode, enabling a hearing-impaired individual to freely use the SLR smartphone application. The dataset was developed with five unique people performing 200 signals from five different points of view under diverse background circumstances, addressing the scarcity of sign language datasets taken in smartphone selfies. In the video, each sign had around 60 frames. CNN training use three separate sample sizes, each including a varying number of persons and perspectives. The last two samples are used to evaluate the trained CNN.

Recognition of static sign language by deep learning [4]. The objective of the project was to develop a system capable of translating static sign language into its corresponding word counterparts, including letters, numerals, or fundamental static signals, to familiarize individuals with the fundamentals of sign language. The researchers established an assessment technique and performed many tests to validate the significance of the system's non-signer functionalities. The solution received high marks for usability and learning efficacy throughout the evaluation.

A Comprehensive Study on Deep Learning-Based Methods for Sign Language Recognition [5]. A comparative experimental evaluation is conducted on computer vision-based sign language recognition systems. Recent deep neural network methodologies in this domain are used to conduct a comprehensive assessment of various publically accessible datasets. This project aims to enhance sign language recognition by mapping non-segmented video streams to glosses. This paper presents two novel sequence training criteria derived from the fields of voice and scene text recognition.

A deep learning-based method for recognizing static sign language signals [6]. The research discusses the use of deep learning via convolutional neural networks for the accurate identification of static signals in sign language recognition. This research amassed 35,000 photographs of signs, with each image depicting 100 static signs, contributed by diverse users. The proposed system's efficacy is evaluated on around 50 CNN models. Sign language is a complex and intricate system that relies on computer vision to interpret messages produced by hand motions with face expressions. It is a natural language used by those with hearing impairment to communicate. Sign language employs diverse hand gestures to convey letters, words, or sentences. We provide a pragmatic method for identifying ISL numbers, letters, and phrases in commonplace contexts. The suggested CNN design first employs convolutional layers, followed by ReLU and max-pooling layers.

Recognition of British Sign Language by Transfer Learning to American Sign Language using Late Fusion of Computer Vision and Leap Motion [7]. Researchers conducted many tests in both British and American Sign Language, emphasizing solitary sensory and multimodal methodologies. The results indicate that a multimodal approach surpasses the two individual sensors in training and classifying unknown inputs. This work included a preliminary transfer learning experiment from a substantial BSL dataset to a medium-sized ASL dataset, whereby the multimodality model was identified as the most effective for ASL classification after the transfer of weights from the BSL model. This research benchmarked and assessed all network topologies that were trained, compared, and ultimately fused to achieve multimodality for the first time. The precise classification of sign language, especially with unobserved data, enables autonomous completion of the process, offering a computerized method for interpreting non-spoken language in scenarios where interpretation is required yet inaccessible.

The mArSL Database and Pilot Study: Advancing Hybrid Multimodal Recognition of Manual and Non-Manual Arabic Sign Language [8].A novel multi-modality ArSL dataset that integrates many modalities. The dataset consists of 6,748 video samples captured using Kinect V2 sensors, with fifty signs shown by four signers. This dataset will enable researchers to formulate and evaluate their approaches to advance the field. Furthermore, we used cutting-edge deep learning algorithms to examine the amalgamation of spatial and temporal attributes of various modalities, both manual and non-manual, for sign language recognition.

Recognition System for Thai Finger-Spelling Sign Language Using Deep Learning and Multi-Stroke Techniques [9].A vision-based methodology was used to achieve semantic segmentation via dilated convolution for hand segmentation, optical flow separation for hand strokes, and feature learning and classification through a convolutional neural network (CNN). The five CNN architectures that dictate the forms were then compared. The initial format employed 64 filters, each measuring 3x3, across 7 layers; the subsequent format utilized 128 filters, also 3x3 in size, with 7 layers; the third format incrementally increased the number of filters while maintaining 7 layers, all featuring a uniform 3x3 filter size; the fourth format mirrored this structure; the final format was a structured configuration.

Utilizing k-Nearest Neighbors with Dynamic Time Warping and Convolutional Neural Network algorithms in wearable technology for sign language recognition [10]. The research includes a wearable electronics-based device for sign language recognition that utilizes two separate classification algorithms. The wearable electronics captured finger, wrist, and arm/forearm movements with a sensory glove and inertial measurement units. k-Nearest Neighbors using Dynamic Time Warping (a non-parametric methodology) and Convolutional Neural Networks used as classifiers (a parametric method) were implemented. Ten sign-words from Italian Sign Language were analyzed, including cose, grazie, and maestra, alongside globally recognized phrases such as google, internet, jogging, pizza, television, twitter, and ciao. Seven individuals, including five males and two females, aged 29 to 54 years, each replicated the signals 100 times (SD).

A discrete time sliding mode controller (DSMC) is proposed for higher solicitation not withstanding defer time (HOPDT) frames [11]. As portion of structure states and botch, a sliding mode surface is selected and the tuning parameters of the sliding mode controller are resolved using overpowering post circumstance scheme. The control object for "ball in a barrel" is to handle the velocity of a fan blowing air into a chamber to keep a ball suspended in the barrel at a certain predestined position. The DSMC is attempted to coordinate the ball's position subsequently. But skillfully clear, this is a troublesome control issue due to the non-direct ramifications for the ball and the confounding material scienceT regulating its lead. The DSMC is attempted to coordinateTtheT ball's position subsequently.

The fine-tuned PID controller have proposed for the air levitation system [12]. Advanced genetic algorithm is used for tuning parameters of PID controllers. For demonstration of efficiency and applicability of the proposed PID controller, simulation-based experimentations have been conducted. The proposed PID design method has been linked with other three optimisation techniques. Ant colony optimisation, particle swarm optimisation and fuzzy logic have been used for performances comparison of advanced genetic algorithm-based PID controllers. In experimental results, we have got very smallest value of IAE, ISE and ITAE using proposed method. It indicates that the proposed PID design method offers better performances than other three optimisation-based PID design methods and other existing methods.

METHODOLOGY

System Architecture

The proposed IPL score prediction system is designed using a modular pipeline that leverages deep learning and structured historical cricket data. The architecture comprises five key modules: data collection, preprocessing, model development, prediction, and evaluation. Each module plays a critical role in ensuring accurate and context-aware match score predictions

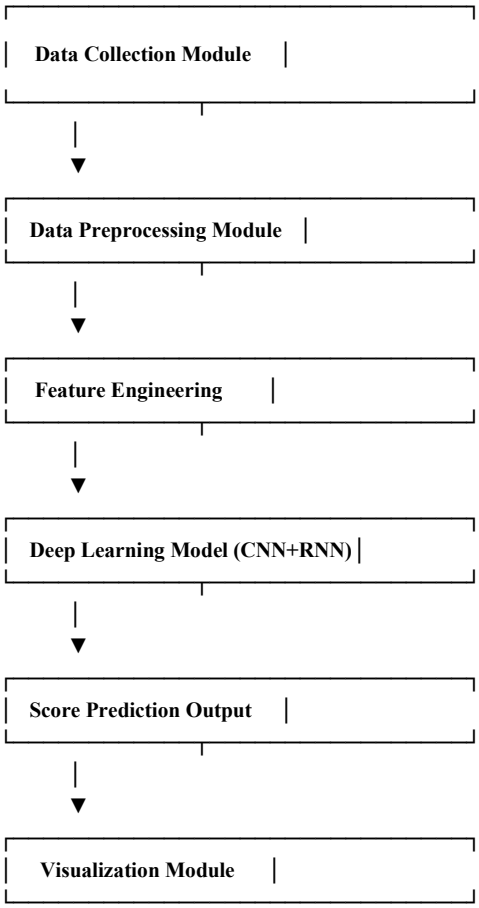

Figure 1: System Architecture

Visualizations were created to compare predicted scores with actual match outcomes. The proposed model was also benchmarked against traditional ML methods (Linear Regression, Random Forest, XGBoost), with the deep learning model showing superior performance, particularly in capturing run-rate fluctuations and momentum shifts.

Module 1: Data Collection

Historical data from official cricket databases such as Kaggle and ESPN Cricinfo was gathered. The dataset includes match-specific details (venue, date, teams), ball-by-ball sequences (runs, wickets), and player-level statistics (strike rate, economy, recent form). This diverse data foundation enables comprehensive learning and contextual modeling.

Module 2: Data Preprocessing

To enhance model performance and generalization:

- Data Cleaning: Inconsistencies, null values, and duplicates were removed.
- Categorical Encoding: One-hot and label encoding were applied to categorical variables such as team names, venue, and toss decisions.
- Feature Engineering: Additional features like cumulative run rate, wicket momentum, and recent over scores were derived.
- Normalization: Continuous variables were scaled using Min-Max normalization to standardize input across the neural network.
- Data Splitting: The dataset was split into training (70%) and testing (30%) sets for model evaluation.

Module 3: Model Development

A hybrid deep learning architecture combining CNN and LSTM was constructed:

- Convolutional Layers: Capture spatial relationships among structured match inputs, such as team-vs-team performance matrices.
- LSTM Layers: Learn sequential dependencies over time (e.g., score progression across overs).
- Flatten and Dense Layers: Extracted features are flattened and passed through fully connected layers for final regression.
- Dropout Layer: Applied to prevent overfitting.
- Activation Functions: ReLU for hidden layers; linear activation for the output.
- Loss Function: Mean Squared Error (MSE) was used for score prediction.

Module 4: Prediction Phase

In real-time applications:

- The user inputs current match parameters (overs, score, wickets, batting/bowling team).
- These are preprocessed and reshaped to match the model input dimensions.
- The trained model predicts the final score using historical patterns and current context.
- The predicted output is presented with an optional confidence interval.

Figure 2.Epoch vs Loss & Validation Loss

Module 5: Evaluation and Analysis

Performance was assessed using:

- Mean Absolute Error (MAE)

$$MAE=n1\sum i=1n|xi-yi|$$

where*:*

- xi represents the actual or observed value for the i-th data point.
- yi represents the predicted value for the i-th data point.

- Root Mean Square Error (RMSE)

$$RMSE=n1\sum i=1n(xi-yi)2$$

Where:

- RMSE is the Root Mean Squared Error.
- xi represents the actual or observed value for the i-th data point.
- yi represents the predicted value for the i-th data point.

RESULTS

The result images shown below illustrate the classification performance of the proposed system. These visual outputs represent how the model distributes and categorizes input data across various prediction scenarios. The proposed methodology, which integrates Convolutional Neural Networks (CNNs), demonstrates consistently high accuracy. The system was trained on historical input data, and its performance was evaluated using multiple deep learning classification models.

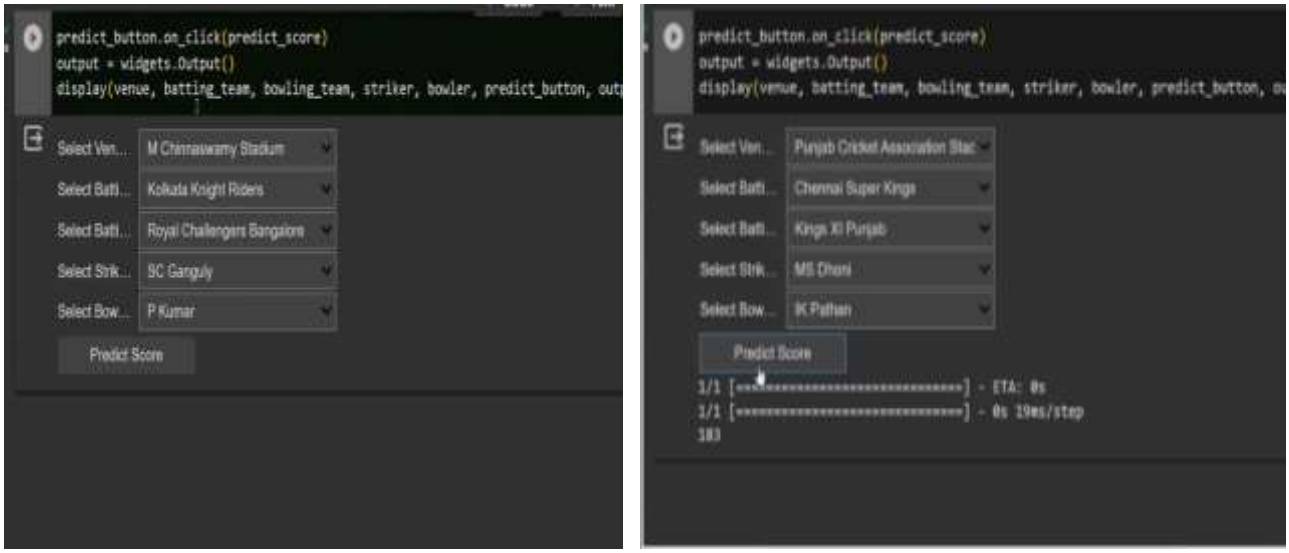

Figure 3 Result with Prediction

Figure 3.Iillustrates a real-time assessment of the proposed model. The model demonstrates its capability to accurately predict the final IPL match score based on live match input parameters such as overs, wickets, and run rate.

CONCLUSION:

The proposed system effectively predicts the final scores of IPL matches by analyzing various input parameters under diverse match conditions. The model is robust to variations such as pitch type, player form, and match pace. To ensure accurate predictions, the system dynamically extracts relevant features from historical and real-time match data. A Convolutional Neural Network (CNN)-based architecture is employed for learning intricate relationships among input features. The system extracts meaningful statistical patterns, including scoring trends and momentum shifts, which enhance the accuracy of predictions. This approach can be integrated with various deep learning frameworks and consistently achieves high prediction accuracy due to the CNN's capability to learn complex, non-linear relationships in structured sports data.

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