Cricket Score and Team Prediction Using Modified CNN with Densenet Framework

M. Chandru, Dr. S. Prasath

Assistant Professor, Department of Artificial Intelligence and Data Science, VET Institute of Arts and Science (Co-education) College, India

This research integrates the Modified Convolutional Neural Network (MCNN) with DenseNet for cricket score prediction. Convolutional Neural Network (CNN) recognizes data patterns; permits feature utility and efficient learning. Incorporation of MCNN and DenseNet captures the complex patterns in cricket match data such as the performance of player, background of team, and match status. Enhanced feature flow lowers overfitting as well as improve accuracy prediction. The proposed model has exhibited better results than traditional prediction models, while testing the model using larger dataset of cricket match scores. The proposed method provides a reliable tool for cricket score prediction in real-time. In case of bowler's assessment, this proposed model has resulted in 99.92% accuracy rate. Meanwhile, accuracy value of 99.95% is attained in the performance of players. This research highlights the capability of integrating MCNN and DenseNet for accurate score cricket prediction.
Keywords: DenseNet, Cricket, Modified Convolutional Neural Network, Player's performance, Score prediction.

1. Introduction

In India, cricket represents a religion rather than game. As cricket is played with bat and ball, it is an outdoor game. Originated in England at the end of the 16th century, this sport has been declared as the national one in 18th century and later well-known in the 19th and 20th centuries [1-2]. In early 1700s, Englishmen have arrived to India with cricket. India has found the first cricket club in 1848. Finally, the Europeans invited the Parses to participate in this match. There are many types of cricket, including test cricket; the cricket lasts for five days [3-4], in which each day necessitates 90 over. Two teams of eleven players compete in this cricket game. The result of toss—that is, flipping a coin and requesting that its face rest on the ground—determines which team has to do batting and bowling against the other. The tossed side chooses to bat first or ball first [5-6]. Performance criteria like consistency, form, venue, opponent, and weather help to choose the teams. Although the bowlers on same side have influence in the runs scored by their team's batter, the batsman's goal is to score high. The performance measure is determined by four primary elements: the efficient performance of the player carried throughout their career; the proficient performance of the players in last few months, and the player's performance in relation to their opponent [7-8].

A cricket match consists of two teams, each with eleven players. Cricket has numerous formats, including test matches like one-day internationals, and 20-20. In India, the beginning with the prediction of cricket match thrilling outcome by focusing on 20-20 matches Premier League (IPL), the most popular kind of game. With six balls in each of twenty over, 20-20 match format calls for each side to have twenty over [9-10]. In 17th century, English colonies has introduced cricket in North America; trade and colonialism has encouraged it to spread further. The International Cricket Council (ICC) wields influence over the game. A cricket match has the chance to end with no result, a tie or win. While one side scores more runs than the other, every inning concludes with the victory announcement. In the case of both teams scoring equal ruin numbers, the last batting team complete their innings and the game is declared a draw. If the game deviates from its intended outcome, a draw or no outcome occurs. Certain limited-over systems use a super over or bowl-out to determine the victor of tie match. A draw [15] is the result when there is no clearance in victory or tie. Wisdom of crowds is an idea, which captures the whole view of varied and sizable population. Most of the times, this material prove to be more valuable than professional opinion. Several researches have focused on utilizing this idea to create forecasts. With two to three billion players worldwide, cricket is the second most often played sport after soccer [20].

2. Background study

Awan, M. J., et al. (2021) provided a model that relied on inputs from the ongoing game, to determine the victor of cricket matches. From the Linear Regression (LR) model, these authors had found that their greatest accuracy was obtained. Using the Spark Machine Learning (ML) framework, it provided 96% accuracy in terms of prediction analysis, therefore indicated the relative efficiency of their model throughout the predictive process. Since the other models lack high accuracy in confusion matrix and R mean squared error, they also exhibit the outstanding results. Both the models have an exceptional overall performance so that one had been utilized in any game to project the winner. Applying certain analytical tools to the dataset helped in training the model; in case of overall dataset deviated from the true data, overall accuracy had not been excellent.

Bharadwaj, F., et al. (2024) implied that the algorithms like ensemble techniques and Decision Trees (DT) were great at forecasting cricket players' performances; as they fared better than Naïve Bayes (NB) and Support Vector Machine (SVM) classifiers,. To improve the accuracy of predictions and aid administrative and coaching decisions about cricket, cutting-edge ML methods in sports analytics, such as Random Forests (RF) and DT were utilized.

Dubey, P. K., et al. (2020) proposed the techniques and other ideas had to be evaluated by utilizing the larger and more representative data set. This had been the next step towards improving prediction accuracy. Other elements like venue, pitch quality, and weather were expanded. Deep Neural Networks (DNN) assisted in considerable accuracy improvement. Models for football, kabaddi, Olympics, and the Asian Games were similar. The authors had improved the accuracy of their model even more by combining unsupervised and reinforcement learning techniques.

Goel, R., et al. (2021) Although their research focuses on IPL Twenty20 events only, same method had been used to project the outcomes of various cricket events, such as test matches and One-Day Internationals (ODI). These categories of classification are used in various sports, including tennis and football, but their specific applications had varied depending on the activity. The writers also wanted to address the results of cancelled matches due to weather.

Haq, I. U., et al. (2023) built a model using ML techniques that was capable of forecasting the result of ODI match before its commencement. Dataset contained ODI match statistics of ODI that came after July 2019. Those authors chose eight main characteristics with the greatest potential prediction accuracy. Following careful study of every publication, these authors discovered the each main element raising their forecast accuracy. The model was based on past match statistics between the teams. This effort consisted of accuracy checks and efficiency.

Kapadiya, C., et al. (2020) created a ML algorithm based on cricket statistics and meteorological data. The design and development of intelligent system to anticipate the cricketer's performance in one-day internationals had to be taken into account other than bowling and batting. A critical factor, weather had significant impact on player performance. These authors recommended data balancing as the pretreatment before adopting ML algorithms since pooled data typically had unequal characteristics. They tested their model on the balanced dataset of meteorological and cricket events, used a unique weighted random forest classifier that allowed hyperparameter tuning.

Karthik, K., et al. (2021) used a feed-forward Deep Neural Network (DNN) classifier to forecast the Dream11 contest's winning positions. Its performance was compared with several types of currently used ML techniques. Using a real dataset, the candidates had developed and utilized the Dream11 app for experimental assessments during 2019 Indian Premier League. Effective generalization of DNN classifier was achieved by the efficient data preparation approaches such as preprocessing and missing data management, resulted in the predicted results. The results showed that DNN-based model accurately predicted the first, second, and third place winner in fantasy cricket leagues, outperformed current ML approaches by almost 13, 8, and 9%, respectively.

Mustafa, R. U., et al. (2017) these authors investigated the efficiency of ML methods performed on collective knowledge acquired from social networks for forecasting the real world occurrences. Beginning with the performance, these authors projected the result of cricket matches using a novel approach. Applying extensive data analysis, these authors found nearly 75% accurate predictions. These authors confirmed their approach on the games participated in IPL 2014 and CWC2015. Moreover, these authors discover that SVM performs better than other classifiers like NB and LR. Therefore, this approach had been extended for the prediction of other Cricket match.

Table 1: Comparison table on various methodologies in cricket score prediction

Author(s) & Year	Objective	Algorithms Used	Key Findings	Metrics/ Performance
Ahmed, R., et al. (2022)	Predicting first-inning IPL scores	LR, Ridge Regression	Used RMSE, MSE, and MAE to determine the best algorithm for accurate score prediction.	Error metrics used to validate model; graphs showed relationships between match factors.
Jayalath, K. P. (2018)	Identifying ODI predictors and modeling match outcomes	LR, Classification and Regression Tree (CART)	Home-field advantage is important for many teams; South Africa had the highest win rate (72%).	Incorporated factors like day or night games and continent.
Jayanth, S. B., et al. (2018)	Predicting cricket match outcomes, team analysis, and player recommendations	SVM (Linear, Poly, RBF), K-Means, KNN	SVM with RBF outperformed others for outcome prediction; clustering used for player recommendations.	Precision and recall metrics; addressed non-linearly separable datasets.
Kevin, S., et al. (2023)	T20 cricket score prediction	XGBoost	MAE of 12.34 and R^2 of 0.85; emphasized the role of contextual and historical match data.	Developed a user-friendly Streamlit interface for predictions.
Rehman, Z. U., et al. (2022)	Player selection and performance modeling	RF	RF had been the most accurate; suggested format-specific player attributes for future models.	Proposed location- and condition-specific parameters for improved accuracy.
Robel, M., et al. (2024)	Assessing player performance and squad selection	LR, Support Vector Regression (SVR), RF	Performance scores used for squad selection; gathered data from espncricinfo and cricbuzz.	Integrated squad predictions for national and franchise teams.
Subasingha, S. A. D. P., et al.(2019)	Predicting ODI victory probabilities and game progression	NB	Predicted winning chances and game progression; developed CRIC-Win Predictor.	High accuracy in winner prediction; included factors like toss effect and ground conditions.
Suguna, R., et al. (2023)	Sports analytics for score prediction and player classification	RF Regressor, XGBoost	RF Regressor and XGBoost were best for score prediction and player classification, respectively.	Introduced new metrics like batting basra and bowling basra.
Weeraddana, N. I. M. M. I., et al. (2021)	Winning probability prediction and next-over score prediction	XGBoost, LR, SVM, KNN	XGBoost outperformed others for winning probability and score prediction.	Accuracy of 84.4% for winning probability; MSE of 1.41 for score prediction.
Wickramasinghe, I. (2020)	Predicting ODI winners	NB	Achieved 85.71% accuracy with univariate feature selection.	Highlighted the need for large datasets and better feature selection.

3. Proposed Methodology

In this chapter, a strategy is proposed for selecting cricket teams and predicting match scores. Here, major emphasis is on ML techniques for feature selection and classification. The procedure begins with the usage of Modified Convolutional Neural Network (MCNN) with Densenet to identify the most related characteristics, which are later fed into the models such as DNN, K-Nearest Neighbor (KNN) and RF, predicting the outcome of match. This part covers everything from the earliest data collection to the final model evaluation

3.1 Data Collection

This study makes use of data obtained from the Kaggle repository. This file contains information from almost 500+ cricket matches. Detailed Bowling Statistics, Bowl.csv, such as runs surrendered, maiden, economy, wickets, match date, player name has 30 columns for bowling, whereas Bat.csv, the detailed Batting Statistics possess 28 columns such as runs scored, 4- and 6-hitters, balls faced, strike rate, out method and match ID for hitting statistics

3.2 Data Preprocessing

Data preparation is critical for getting the dataset ready for analysis and ensuring the ML model ready. As the dataset contains both numerical and category variables, numerical characteristics are normalized to ensure that the variables are present in same scale, eliminating the biases caused by varying ranges. SVMs and other scale-sensitive algorithms benefit the most from this stage. Min-Max approach aids in normalizing each scale of the characteristics. Every feature X_i, undergoes a Min-Max normalization procedure.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \text{ --------- } (1)$$

In equation 1; X_{min} and X_{max} represent the minimum and maximum values of characteristic X, respectively. X refers to the input data value, which has to be normalized. Between 0 and 1, the normalized value of X is inscribed as X_{norm}.

3.3 Convolutional Neural Network (CNN)

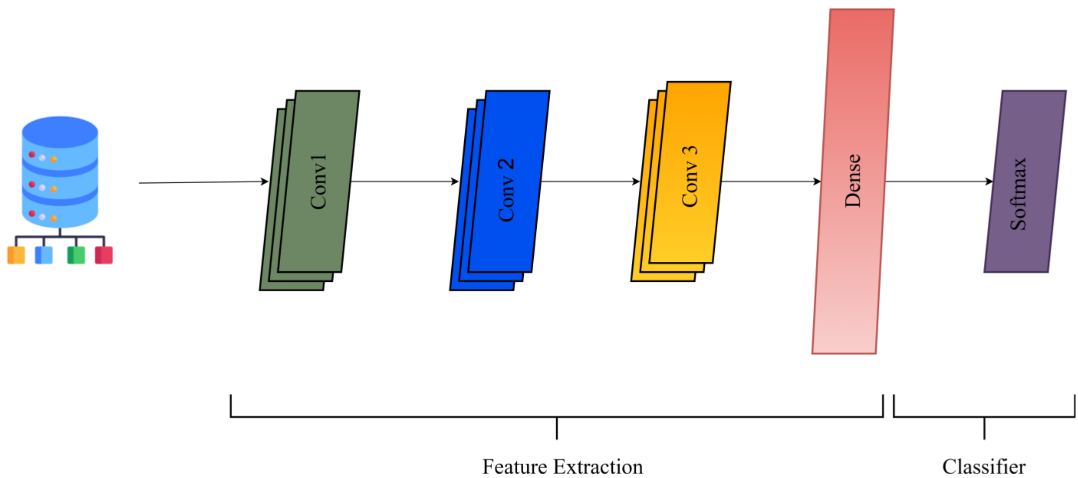

Figure 1: CNN Architecture

The presented CNN model is based on unsupervised learning of concealed ideas; possess the discriminating capacity necessary for proper categorization. In two distinct phases, the feature representation of teams and classifier training corresponding to the representations is carried out. CNN beats the previous two-stage methods in the wide range of applications like image classification, and it learns both the classifier and discriminative feature representations at the similar time. Cricket match is not yet forecast using CNN model. Thus, CNN model is utilized to anticipate the outcomes of cricket matches.

This technique primarily seeks in transferring each player's feature representation from the real feature space to the discriminative space. Later, for acquiring the team representation in space, discriminative representations of every player is gathered. At last, classifier is applied to these discriminated representations. Under the end-end manner, the classifier and its representations are learnt.

The convolutional block is the starting layer of CNN, consisting of two further convolutional blocks followed by the linear classification layer. The batch normalization layer comes after the corrected linear non-linearity layer generated by each convolution block. The two teams' combined feature representations drive the design. The major goal first convolutional block is to assemble the data at player level.

The average pooling layer generates two team-level feature vectors from each team's individual player data. To grasp the team-level discriminative information, second convolutional block evaluates team-level features. The combined input data from x two teams is later transmitted to the linear classifier via the third convolutional block, where it is aggregated into a single discriminative feature vector.

$$\hat{Y} = \mathrm{Softmax}\left(\mathrm{FC}\left(\mathrm{GAP}\big(\mathrm{Conv}\,(X)\big)\right)\right) \text{------------ (2)}$$

This equation 2 represents the CNN used in cricket score prediction, of which X refers to the input features like players score and information about the game is processed through convolution layers,(Conv(X,). Later, it is summarized by Global Average Pooling; indicated as GAP, passes through the Fully Connected (FC) layer, and finally converts to the probabilities using Softmax in score prediction. The variable $\hat{Y}$ indicates the predicted probability distribution along the CNN produced classes. Softmax is the function that performs the conversion of scores into probabilities.

3.4 DenseNet

DenseNet performs best on the numerical classification challenge. And so, it is utilized for the player's feature extraction. This model has certainly performed better than the other pre-trained models. This research uses DenseNet as the feature extraction model.

DenseNet has created a more complex network with dense connections. The dense block layer, which focuses on the efficient information flow betwixt network layer, serves as the most essential important component of the model. In this system, layers receive input from lower levels and feature mappings to higher levels. In case of automatic feature reuse, precise connections in the middle of layers alongside the input and output, enables the effective transfer of older features to the subsequent ones. This network topology has been used for extracting highly common and significant properties after the precise and effective training.

$$\hat{Y} = \mathrm{Softmax}\left(\mathrm{FC}\left(\mathrm{GAP}\big(\mathrm{DenseNet}\,(X)\big)\right)\right) \text{------------- (3)}$$

This equation 3 refers to the DenseNet model for cricket score prediction. The predicted cricket score, represented as probabilities for different possible outcomes is referred as $\hat{Y}$. Towards the densely connected layers of DenseNet, the input features X, such as player's state, condition of the game is fed. DenseNet model processing the input X is inscribed as

DenseNet (X). Passing through the Fully Connected (FC) layer, GAP lowers the input. Consequently, Softmax function gives the outputs of predicted cricket score probabilities.

MCNN with DenseNet

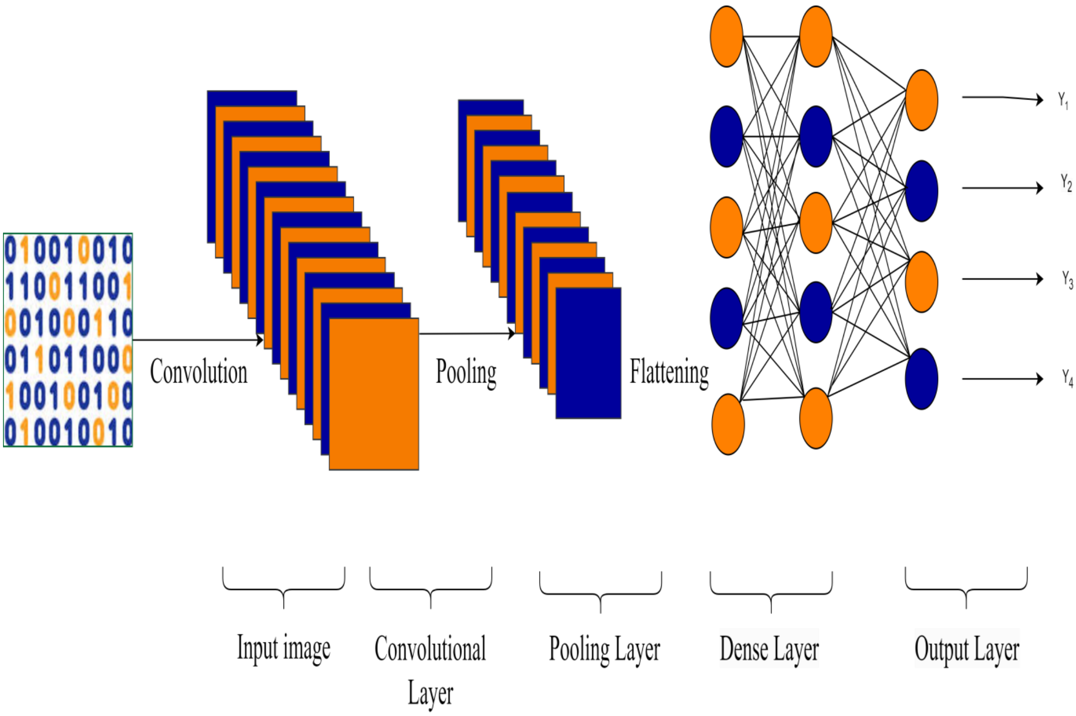

Figure 2: MCNN with DenseNet Architecture

Combining MCNN with DenseNet involves exploiting the custom flexibility of CNN with the efficient feature reuse of DenseNet. MCNN acts as the initial feature extractor, uses convolutional layers, batch normalization, ReLU activation, and pooling to process input images into feature maps. DenseNet block creates the stack of densely linked layers from these feature maps by combining inputs from each layer below. Between DenseNet blocks, transition layers such as comprising convolution, batch normalization, and pooling, reduce the dimensions for efficiency. GAP layers following DenseNet processing and feature maps are reduced to vector form. Finally, completely connected layers are used for the purpose of classification or regression. By combining these two architectures, model benefit from the customized feature extraction of MCNN and DenseNet's efficient parameter usage and deep representation learning. This hybrid approach is effective for numerical-related tasks, balancing performance and computational complexity. The input is inscribed as X, and the MCNN transforms it into feature maps F_{CNN} through the operation such as:

$$F_{CNN} = \mathrm{Pool}\left(\mathrm{ReLU}\left(\mathrm{Conv}(X)\right)\right) \text{ -------------- (4)}$$

Under equation 4, Conv(X) applies the convolution method to obtain local patterns, such as edges or texture, from input X. A non-linear activation function called as the Rectified Linear Unit (ReLU) is used to teach the network to learn complicated characteristics and Pool, the spatial dimensions of feature maps, retains the most critical information while simplifying the calculations.

These feature maps are fed into a DenseNet block, which uses dense connections to encourage feature reuse. A DenseNet block with n layers connects each layer's output of i-th layer, H_i to the subsequent layers.

$H_i = f_i\ ([H_0, H_1, \ldots\ldots, H_{i-1}])$ -------------- (5)

Convolution function f_i is applied for the concatenation of preceding layer outputs. Before the initial input, the constructed whole DenseNet block layers are shown as H_0, $H_1, \ldots\ldots, H_{i-1}$, allowing for feature reuse. The output in the current step i is written as H_i.

Transition layers in DenseNet reduce the dimensions through pooling and 1×1 convolutions. The output of DenseNet block $F_{DenseNet}$, is passed through Global Average Pooling (GAP) to reduce the spatial dimensions:

F_{GAP} = GAP $(F_{DenseNet})$ ------------ (6)

The output $F_{DenseNet}$ reduces the spatial dimensions to a single value per feature, resulting in the compact vector F_{GAP}, which represents the most important global features for final prediction.

$\hat{Y} = \mathrm{Softmax}\left(\mathrm{FC}(F_{GAP})\right)$ ------------- (7)

The final prediction $\hat{Y}$ is generated by applying Softmax function to the output of the Fully Connected (FC) layer, converting it into probabilities for each class.

4. Result and Discussion

This section assesses the selected cricket teams and foretells their cricket scores accurately. The final result of Kaggle dataset usage reveals that the proposed model has exhibited efficient performance in predicting the outcomes of cricket match.

Table 2: Comparison of bowler's performance metrics across different algorithms

Algorithm / methods	Accuracy	Precision	Recall	F-measure
KNN	98.84	97.21	97.59	96.08
DNN	99.80	96.18	97.48	96.45
RF	99.67	96.53	98.76	97.88
CNN	98.63	97.15	99	97.69
MCNN with DenseNet	99.92	98.72	99.01	98.10

Table 2 compares the performance of bowlers using the different algorithms. The methods include KNN, DNN, RF, CNN and MCNN with DenseNet. The values of F-measure, recall, accuracy, and precision are assessed. Among the methods, KNN has the lowest F-measure but highest accuracy. While DNN excels in accuracy, it falls short in precision and recall. RF measurements suggest good performance; nevertheless, recall is where it truly excels. CNN has the good recollection but rather low accuracy. In terms of accuracy and overall performance, MCNN with DenseNet outperforms its competitors. Thus, the players namely Harbhajan Singh, Nazmul Hossain, Zaheer Khan, Abdul Razzaq, Yuvraj Singh are predicted as the best bowlers.

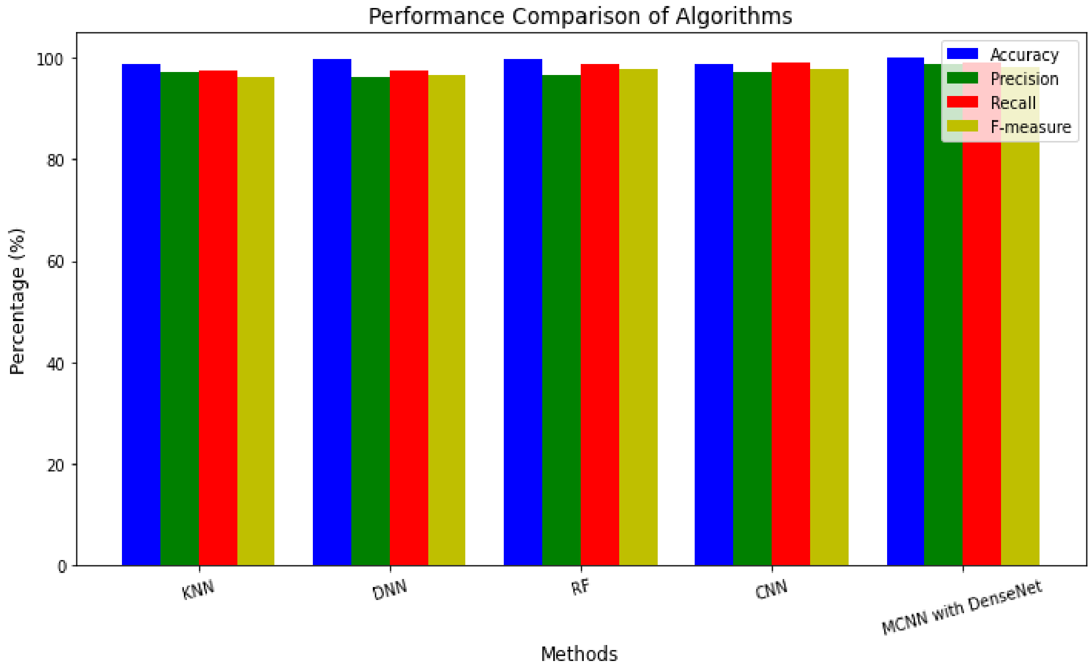

Figure 3: Comparison chart of bowler's Performance metrics

Among the algorithms like KNN, DNN, RF, CNN, and MCNN with DenseNet, the accuracy, precision, recall, and F-measures values are compared in Figure 3. The performance of every algorithm is indicated by four bars. Consequently, MCNN with DenseNet beats the others algorithms.

Table 3: Comparison of player's performance metrics among various algorithms

Algorithm / methods	Accuracy	Precision	Recall	measure
KNN	99.77	97.12	97.22	96.68
DNN	98.82	97.23	98.79	97.99
RF	99.46	96.55	98.45	96.11
CNN	98.33	96.76	97.34	97.39
MCNN with DenseNet	99.95	98.65	99.04	98.13

Table 3 compares the performance of the five algorithms based on F-measure, recall, accuracy, and precision metrics. Despite having a slight lower F-measure, KNN outperforms the competition in accuracy. DNN is a formidable opponent, with respectable recall and F-measure scores. RF achieves the balance of accuracy and recall by having a significantly low F-measure value. As a whole, CNN performs well, lacking precision when compared to other approaches. MCNN with DenseNet protrude by consistently achieving the highest levels of accuracy and metrics. Consequently, Khaled Mahmud, Mushfiqur Rahman, Habibul Bashar, Joginder Sharma, Khaled Mashud and Ajit Agarkar are predicted as the outstanding players.

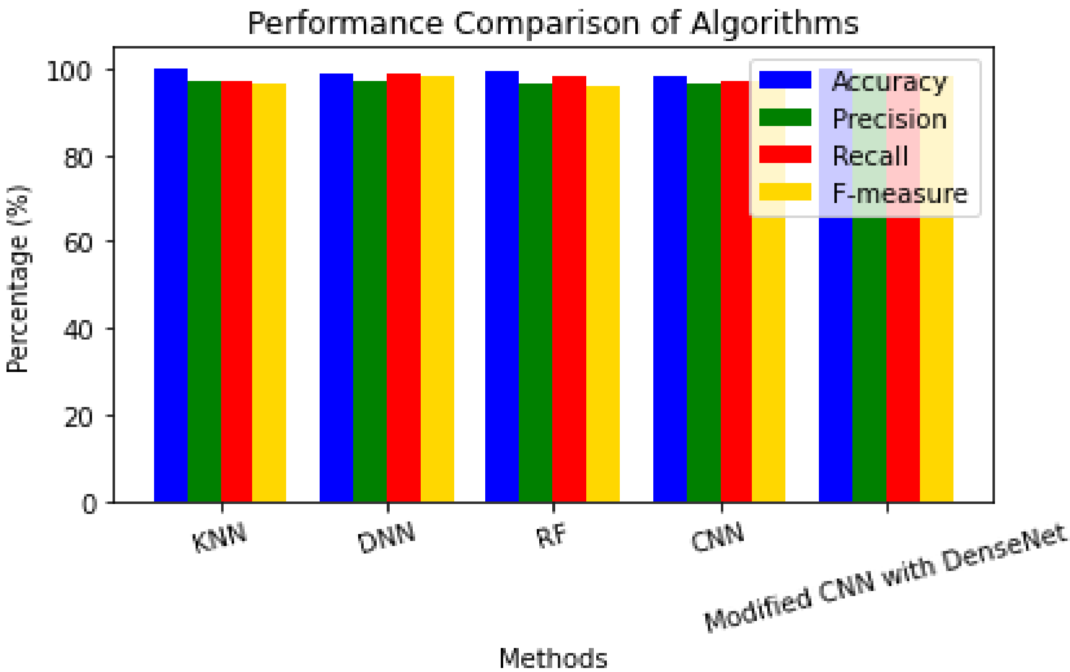

Figure 4: Comparison chart of player's performance

Figure 4 depicts the performance of player along the five algorithms: KNN, DNN, RF, CNN, and M CNN utilizing DenseNet, with F-measure, recall, accuracy, and precision shown. Each set of bars represents the performance percentage of a single algorithm. The MCNN with DenseNet outperforms its competition in all aspects. Although the other approaches offer competitive outcomes, their costs are significantly cheaper.

5. Conclusion

In this research, MCNN with DenseNet is proposed for the accurate prediction of cricket scores. Compared to the other methods, MCNN with DenseNet has exhibited the outstanding performance. Likewise, the model has also attained the accuracy, precision, recall, and F-measure in high percentage. The model's precision rate of 98.65% elucidates the efficient neglect of false positive whereas its 99.95% accuracy vale indicates its effectiveness in score prediction. The additional values like 99.04% recall and 98.13% F-measure indicates the capability of finding true positives and highlighting the precision, recall balance. The incorporation of DenseNet maximizes feature extraction and predicting proficiency, leading to the superior results. The proposed method has surpassed the traditional CNN and other algorithms, exhibiting generalization over the different datasets. Due to its persistent performance along the metrics, model serves as a reliable choice for the predictions demanding high accuracy and robustness.

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