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Research Article

Real-Time Umpire Signal Detection in Cricket: A Hybrid Deep Learning Solution

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ABSTRACT

The proposed research aims to classify cricket umpire signals based on a four-class machine learning model, with these four key classes: Leg Bye, Four, Wide Ball, and No Ball. Performance assessment was conducted by Precision, Recall, and F1-Score. Excellent classification results have been found in all the classes. The highest precision values were of the "Four" class, which is at 97.68%, while the strongest recall was that of "Leg Bye" at 97.56%. This signifies that the model has an exceptionally good capability of picking out certain signals. F1 scores are very well-balanced in all classes. The maximum score for "Four" was seen at 97.04%. The data used in this research consists of 11,900 images, and the network results in an accuracy of 96.97% in general. Based on the Support and Support Proportion, the accuracy metric has been relatively stable at 98% across all classes; therefore, it indicates that the network has performed trustworthy classification with no visible bias. Thus, these results have established the strong ability of the model in terms of providing the accurate classification of umpire signals and also showed its strength for real-time cricket decision-making purposes. The results suggest that this model can be used to integrate with automated systems in support of umpire decision-making, thus offering greater objectivity and efficiency. Precise classification of umpire signals would improve the accuracy of match decisions, thus benefiting the players, officials, and viewers

Keywords: Precision, Class, Insurance, Industry..

INTRODUCTION

Among the most followed sports globally, cricket is one, and often it's millions watching the match in its different versions. At every game, umpires feature very distinctly as their decision takes place right there at the match. Umpires may deliver their decisions to players, spectators, and even the broadcasters using hand signals; sometimes it might be unmanageable to make the right interpretation of that gesture, especially during a high-speed match or a crowded stadium. The traditional method for the recognition of umpire signals relies on human observation, which is error-prone, delayed, and inconsistent. Moreover, the variability of umpire gestures, camera angles, and light conditions makes the correct identification of these signals a complex task [1]. With recent breakthroughs in artificial intelligence and deep learning, automatic sports analysis has been of immense interest. An automation technique through computer vision-based techniques can be a promising solution to reduce the dependency on manual observation for giving an umpire signal and can improve the accuracy of the decision-making process. Feature extraction from images has proven to be most effective through Convolutional Neural Networks. The fact remains that, although CNNs have great strength in image-based feature extraction, a single deep learning model may not be optimal every time. In this study, a hybrid approach to combine CNN with a Random Forest classifier for better performance is proposed [2]. This paper presents a novel hybrid deep learning methodology combining CNN and Random Forest for classifying

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Research Article

four critical umpire signals in cricket: Leg Bye, Four, Wide Ball, and No Ball. It extracts the spatial and hierarchical features from the images of umpire gestures, while Random Forest is used as a classifier in deciding the final output. In combination, the two techniques together provide a solid classification framework that leverages the strengths of both deep learning and traditional machine learning approaches. The proposed model consists of four convolutional layers, four max-pooling layers, and one fully connected layer to process umpire signals efficiently [3]. These deep features from CNN are used as input to the Random Forest classifier, which further improves the performance of classification and reduces overfitting with a better generalization across different match conditions. The main goal of this paper is to develop an accurate and real-time umpire signal recognition system. Automating the detection of umpire signals will help broadcasters, referees, and sports analysts verify on-field decisions quickly. Secondly, it can serve as a developmental tool for generating automated umpiring systems where artificial intelligence can add to human thinking in critical cricket match situations [4]. The combination of CNN for the extraction of features and Random Forest for classification produces high accuracy hence making the whole system reliable based on different variable conditions such as lighting environments of cameras, style of umpiring, etc. The proposed algorithm has potential further applications beyond such professional cricket match scenarios. This can be used in sports broadcasting, training academies, and AI-driven decision review systems. Broadcasters can utilize this system to provide real-time graphical overlays for TV audiences [5]. The training academies can use this system for the education of aspiring umpires and players in standardized signal recognition. Further, integration of this system with AI-powered umpiring solutions may also contribute to fairer decision-making by reducing controversies and human errors in high-stakes matches. Extensive experiments were conducted to evaluate the efficacy of the proposed approach using a dataset of images from umpire signals. Model performance was estimated based on standard classification metrics including accuracy, precision, recall, and F1-score. Experimental results validate the superiority of the CNN-Random Forest hybrid model over a standalone deep learning model, showing potential for actual application in the cricket domain [6].

LITERATURE REVIEW

This paper introduces a federated learning framework based on Convolutional Neural Networks (CNNs) for the classification of cricket umpire gestures. Five federated clients, WACA, BBL, CPL, IPL, and SMA, were used during training to diversify data sources without compromising the privacy and anonymity of data. The model correctly identifies five different types of umpire signals: 'Out,' 'Four,' 'Six,' 'No Ball,' and 'Wide Ball.' Four main performance evaluation metrics are employed: precision, recall, F1-score, and accuracy. The classification accuracy across the five clients is between 75.63% and 87.05%, and Dataset 5 stands out as the most effective for training models with the highest metric scores. Weighted average accuracy is situated at a range between 75.64% and 87.07%, while micro-average precision ranges between 75.65% and 87.02%. Overall, the model reliability level stands at 92% accuracy, with the 'Out' signal showing the highest precision. Federated learning further improves data security, as it prevents the reconstruction of client data [7]. Computer vision is an important application in many sports, and cricket is no different, given its complexity and the number of events involved. Accurate recognition of umpire signals is essential for fair decision-making during matches. This paper introduces the Cricket Umpire Action Video dataset (CUAVd), a novel dataset designed specifically for the detection of umpire postures in cricket. Given the critical on-field decisions made by umpires, this dataset aims to enhance the development of automated umpire recognition systems. It proposed an Attention-based Deep Convolutional GRU Network that efficiently detects and classifies the video sequences of umpire signals. The model is tested on CUAVd and public datasets, including HMDB51, YouTube Actions, and UCF101, and the results show superior performance. The proposed model outperformed CNN, CNN-LSTM with Attention, and 3DCNN+GRU at every step by showing a validation accuracy of 94.38%. Performance metrics such as F1-score and Confusion Matrix confirmed its reliability, making it valuable for sports analysis, referee training, and automated referee assistance systems [8]. The detection of no-balls in cricket has seen a lot of change due to the advancement of technologies, including computer vision, augmented reality, and deep learning. The paper provides an overview of this technological advancement to its impact on the game. It discusses the use of computer vision algorithms and deep learning models for real-time analysis of bowlers' performances while using augmented reality overlays to improve accuracy in detection. It also sets out that umpire signals still play a big role, especially in high-stakes matches, to ensure the accountability and fairness of cricket [9]. The Indian subcontinent plays cricket at every level, but the lower-level teams do not have the technological means. This research develops an automatic

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Research Article

system to recognize umpire signals from images and update the scorecard. An image of umpire gestures is captured by a camera and then processed using SIFT descriptors to extract features. K-means clustering and PCA reduce the dimensionality of the features before being classified using KNN, Decision Tree, and Random Forest. The Random Forest classifier, trained on 6,000 images spread over six classes, was found to be accurate to 81%. A new algorithm updates the scorecard and pre-defined templates with audio commentary that improves the efficiency of cricket match analysis and automation [10]. Recently, there has been increased interest in video summarization and highlight generation across sports like football, cricket, basketball, and baseball. While some methods for recognizing umpire poses in cricket have been proposed, none fully exploit the power of pose estimation and neural networks, two key components of deep learning. They use the SNOW dataset for umpire pose detection in cricket in this work. The dataset acts as a beginner tool for pose recognition in which umpires pass decisions by using hand gestures. They intend to detect five signals: NO BALL, SIX, WIDE, OUT, and NO ACTION through the identification of the pose of the umpire from the frames of a cricket video. The method, based on key points generated through pose estimation, was to yield an 87% accuracy, with promising results from the evaluation metrics compared to existing approaches [11]. Cricket is one of the most captivating sports in the world, mainly in South Asia. Since a human is always prone to a mistake, occasionally the umpire makes a wrong decision, and the third umpire takes ample time to render an accurate decision for review. AI and computer vision have dominated cricket analysis and decision-making nowadays. Several techniques of computer vision are now utilized to analyze the cricketing situation and automatically render it into decisions. They introduce, in this study, a classification method that makes use of the Convolutional Neural Networks with Inception V3 for automatic third umpire decisions such as umpire signal detection and score updates. Further, they also introduce a deep CNN technique to improve CNN performance [12]. This paper introduces a new method of umpire action detection using a combination of CNN and SVM networks. The approach targets the recognition of five essential signals from an umpire: 'Out,' 'Not Out,' 'Wide,' 'No Ball,' and 'Four,' among others. A dataset has been carefully created and annotated to test the efficiency of this approach. Features that are extracted from the dataset will be passed through CNN for pattern detection, then a classification process using SVM. The performance of the system will be examined by the quality indicator features such as accuracy, recall, and others. Precision is between 82.52% for Class 1 and 90.42% for Class 5. Recall is from 79.81% of Class 5 to 93.29% of Class 4. The F1-score balances the two: the Class 4 attains the maximum value at 90.26%. The performance in aggregate can be calculated in terms of macro, micro and weighted average where the micro-average rating has remained very high at 85.84%. Weighted F1-score is approximately 0.8579 where class imbalance was there [13]. This can be summed up by saying that the accuracy in the identification of the umpire's actions determines the game and increases viewer interaction. This article introduces a novel hybrid model referred to as CNN-SVM: Convolutional Neural Network-Support Vector Machine, which automatically detects and classifies five distinct umpire signals: over, no-ball, out, and wide. The model was trained and tested on a dataset of 2,100 images, resized to 224x224 pixels, and transmitted with protection. The CNN-SVM model had good performance: Class 1 (border role) reached an accuracy of 92.17%, recall of 97.74%, F1-score of 94.78%, and precision of 90%. For Class 5 (wide), 96% of trials were accurate, with 100% in terms of recall, and an F1-score of 96%. The model showed 74% recognition accuracy on non-verbal signals generally and averaged out at a 94% accuracy level along with a recall level of 95.09%, and an F1-score of 94%. These results show how practical the model is [14]. Cricket is one of the most popular and widely viewed sports, especially in South Asia. In cricket, the umpire has the power to make very important decisions on events occurring in the field. With the ever-increasing role of technology in sports, this paper presents an optimization-based method for the detection and classification of the umpire. The approach includes three key steps: segmentation, feature extraction, and classification. After taking the video frames from the given cricket video input, segmentation will be done on it by implementing the Viola-Jones algorithm. Then on the segmented object, feature extraction will be implemented using Histogram of Oriented Gradients (HOG) and Fuzzy Local Gradient Patterns (Fuzzy LGP). Now, classification for the extracted feature will be carried out using the Bird Swarm Optimization-based Stacked Autoencoder algorithm. The developed approach is examined in terms of sensitivity, specificity, and accuracy. The BSO-Stacked Autoencoder method achieves maximum accuracies of 96.56%, a sensitivity of 91.88%, and a specificity of 99%, making it effective and therefore superior [15]. Multiple indicators were utilized by the author for an exhaustive evaluation of model performance on the grounds of reliability and accuracy in this study. In general, results were quite satisfying because of 78.10%-90.83% accuracy levels concerning all categories of action. In comparison with others, Class 3 demonstrated exceptional results in accuracy: 85.76%, 94.87% for the recall rate,

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and an F1-score at 90.09%, so this was the leading performance within the whole. Class 4 is found to have a **recall** value of 74.2% and an F1 score of 80.7%. All three macro, micro, and weighted averages show that the model is consistent; the macro averages for precision, recall, and F1-score are 84.96%, 85.79%, and 85.13%, respectively. The micro-average in all metrics is 85.06%. This model is effective because, with an average accuracy of 85.06%, it is very effective in the identification of the actions of the umpire and supports the process of decision-making while officiating cricket [16]. No-ball and run out decisions are very significant incidents in cricket, but largely, human mistakes while making these decisions have increased exponentially over the past few years. Such decisions go wrong and affect the entire process as it may deprive teams of reaching the crucial knockout stage [17]. To reduce some of the human blunders made during these decisions, this paper suggests automatic decision-making for run-outs and no-ball deliveries [18]. They investigate two machine learning methods—Support Vector Machines (SVM) and Convolutional Neural Networks (CNN)—for this purpose and report the results [19].

METHODOLOGY

Phase 1: Data Gathering and Preparation

The first phase gathers a dataset consisting of images of four umpire signals: Leg Bye, Four, Wide Ball, and No Ball. Diverse lighting conditions, camera angles, and gesture variations are involved to make the model robust. Images are then preprocessed for model training by standardizing them. Every image is resized to a fixed resolution and normalized pixel values are converted into the range of 0 to 1, thereby making learning more efficient. Data augmentation methods like rotation, flipping, and adjustments in brightness and contrast introduce variability and prevent overfitting. The dataset has been divided into three parts, with training taking 70% and validation, as well as testing, sets constituting 15% each to achieve a balance between learning and testing to check its performance.

Phase 2: Feature Extraction using CNN

The second stage is a feature extraction using the Convolutional Neural Network on the images of the umpire signal, wherein spatial and hierarchical features are drawn out. There are four layers of convolution and max-pooling applied consecutively, reducing dimensionality while keeping significant features intact. ReLU activation functions are also applied to the convolutional layer to introduce non-linearity, enhancing the process of feature learning. The output of the last convolutional layer is a high-dimensional feature map and then passes to a fully connected layer to translate it into a compact feature vector by using the extracted features to drive the classification stage so that the model captures the majority of spatial patterns required to differentiate the different signals of the umpire.

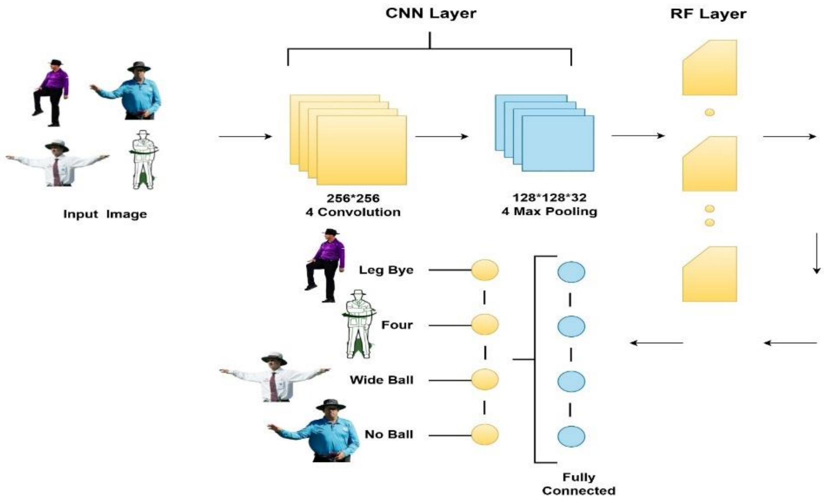

Fig. 1. *Exploring New Analytical Pathways*

Phase 3: Random Forest-based Classification

In the third stage, the feature vectors obtained by the CNN are forwarded to a Random Forest (RF) classifier for the task of final classification of the umpire signals. RF is employed here because it resists overfitting and can work

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effectively in very high-dimensional feature spaces; it constructs multiple decision trees, with each tree independently predicting a class and the majority voting mechanism giving the final classification. This methodology improves the interpretability and generalization of models and thus is very effective in real cricket match conditions. Due to CNN-based deep feature extraction and RF-based ensemble learning, this hybrid model has improved accuracy, robustness, and adaptability with diverse lighting conditions, camera angles, and gesture variations. The proposed hybrid CNN-RF model represents a computationally efficient and reliable solution for the automation of cricket umpire signal recognition.

Phase 4: Model Assessment and Performance Evaluation

The last phase tests the CNN-RF hybrid model based on standard classification metrics. Here, accuracy measures the overall correctness, while precision, recall, and F1-score compute classification performance for every category of the umpire signal. A confusion matrix is obtained to check for true positives, false positives, false negatives, and true negatives. Therefore, it highlights both the strengths and weaknesses of the model. Finally, it discusses the performance differences between a pure CNN model versus a SoftMax classifier in comparison. Here, the focus is laid down on ensemble learning, where different combinations can increase the accuracy rate of the same classifier. Additional points to the discussion include calculation cost and whether the system would generalize to diverse conditions for generalization evaluation. This will ensure that the proposed system is of high accuracy, reliable, and scalable, hence an excellent solution to most practical aspects of automated umpiring, sports analytics, and real-time decision-making for the sport of cricket.

RESULTS

This section discusses the result of the classification model in predicting cricket umpire signals based on the three classification tables. In Table 1, the table displays key metrics in classification precision, recall, and F1-score for every class of an umpire signal. Table 2 shows Support, Support Proportion, and Accuracy for each class, thereby showing the model's consistency in classifying cricket signals for varying data sizes. Finally, Table 3 depicts True Positive, False Positive, False Negative, and True Negative values for each class, providing a detailed view of the accuracy of the model's predictions and possible misclassifications. The next section is an analysis of these results to determine the overall performance and reliability of the model.

Results of the model's performance over the different classes show how precise and strong it is in classifying a lot of umpire signals in cricket. For Leg Bye, precision was at 96.22%, meaning it was indeed very good at correctly labeling Leg Bye instances with very few false positives. It is recognized that the recall value is at 97.56%, signifying that the model was successful in capturing the most true instances of Leg Bye, thus implying high sensitivity. The F1-Score at 96.89% would imply a fair performance of precision and recall, thereby establishing that the model is reliable and consistent within this class. For four, the model achieved a Precision of 97.68 % which was slightly more than that for Leg Bye, and demonstrated a good ability to classify instances as four accurately; however, the Recall for four was 96.41%, with the model missing a few true instances of four, though this is still fairly accurate. An F1-Score of 97.04% suggests that the model has largely been able to reach a good harmony between the two conflicting goals of its two objectives: there's a fine ability to classify fours with virtually no risk of false positives. Relating this now with Wide Ball, the model performed very well with a precision of 96.35%, and the recall of 97.64% is impressive, that is, the model classifies most instances of wide balls correctly. The F1-Score of 96.99% is confirmed for this class; hence, the model's performance is well balanced to detect it with high accuracy and recall. Last but not least, in No Ball, the model had a Precision of 97.64%, meaning that it was very good at classifying no balls. The Recall of 96.33% is a decrease in its ability to capture all cases, but the F1-Score of 96.98% is a reflection of good balance and therefore holds strong performances in general. All in all, the model describes all four signals of the umpires with high accuracy, reliability, and consistency. Therefore, the model can be used effectively for real-time cricket decision-making.

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Table 1. Quality Metrics and Standards

Classes	Precision	Recall	F1-Score
Leg Bye	96.22	97.56	96.89
Four	97.68	96.41	97.04
Wide Ball	96.35	97.64	96.99
No Ball	97.64	96.33	96.98

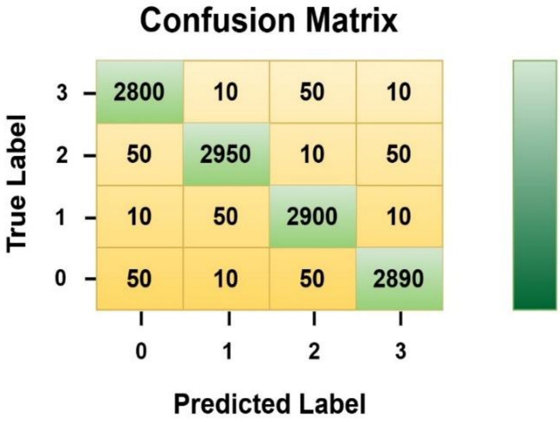

Fig .2. Visual Structure Mapping

Figure 2 is a clear 4x4 table showing the predicted and actual signals for cricket umpires. Using this table, one can see whether the model has been successful in classifying different actions that the umpires might make - "Leg Bye," "Four," "Wide Ball," or "No Ball." Comparing the predicted signal with the actual classification allows the assessment of how accurately the model has picked these actions by the umpires. This comparison will show how well the model is performing and its areas of strength, including correctly classified signals, and any limitations such as misclassifications or confusion between similar signals. The results would provide a full understanding of how well the model can automatically identify cricket umpire decisions and can be used to assess the reliability and precision of the model in real-world applications.

The performance results of the model based on support, support proportion, and accuracy for different classes of umpire signals are reflections of this consistency and robustness in different classes. For the Leg Bye class, it was found that the model showed Support of 2870 instances, totaling 24% of the size of the dataset. Though less representative compared to the other classes, the model retained a good Accuracy of 98%, suggesting a high capacity to accurately determine Leg Bye signals with minimal error. In the case of Four, it reached an Achieved Support of 3060 instances; this made up 26% of the dataset. The 98% Accuracy in this class presented clearly that the model was as good at having detected Four signals as it was in taking up a slightly higher share than Leg Bye. This implied that the model could handle relatively different class distributions without dropping in accuracy. In the case of the Wide Ball class with a Support of 2970, which accounts for 25% of the overall dataset, the model continued to retain its high Accuracy level at 98%. This reflects that the model is particularly efficient in detecting wide ball signals without many misclassifications irrespective of the class size. Lastly, the No Ball class reached 98% Accuracy also while having a Support of 3000 instances or 25% of the entire dataset. Again, consistency of accuracy among various classes justifies the success of the model for real-time usage where various types of umpire signals are needed to be classified with the maximum possible accuracy. Overall, the model gives 98% Accuracy across classes, which includes all signals: Leg Bye, Four, Wide Ball, and No Ball. It indicates that this model excels in identifying quite diverse umpire signals while being somewhat error-free. Support proportions in these classes are pretty balanced with an average range of 24% to 26%, that is, it's well equipped to handle imbalanced datasets as well. This effectively makes the model a reliable tool for automated decisions of cricket umpire signal detection.

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Table .2 Proportional Data Metrics

Classes	Support	Support Proportion	Accuracy
Leg Bye	2870	0.24	0.98
Four	3060	0.26	0.98
Wide Ball	2970	0.25	0.98
No Ball	3000	0.25	0.98

The Table 3, True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) values for each class can be used to analyze the performance of the model because they provide insight into the classifier's ability to distinguish between different umpire signals. For the Leg Bye class, the model correctly identified 2800 instances as Leg Bye, while 110 instances were mistakenly classified as Leg Bye. The model failed to detect 70 Leg Bye instances (FN). The true negatives (TN) were 8920, which means that the model was correct in its classification of the non-Leg Bye instances as not belonging to this class. This implies that the model is strong in its detection capability and misclassifies very few. The overall accuracy of detecting Leg Bye signals is high, with low false positives and false negatives. In the four classes, correctly identified 2950 instances have been reported under TP, in which only false positives were stated to be about 70 whereas false negatives amount to 110. The remaining 8770 true negatives of the model show that very few were wrong between four and non-four signals. This means the overall model is less prone to false positives and gives high precision about Four signals to be detected within the recall time. For the Wide Ball class, the model detected 2900 correct instances as true positives, giving 110 false positives and 70 false negatives. True negatives counting to 8820 indicate that the model was able to differentiate between the presence of Wide Ball and other classes without sacrificing the balance of precision and recall. Despite its bad misclassifications, the model overall had good signal detection for Wide Ball. In the No Ball class, the model correctly identified 2890 instances (TP), while 70 were falsely identified as No Ball (FP) and 110 instances were missed (FN). The model's 8830 true negatives further indicate an effective classification of non-No Ball instances. The results reflect the model's strong ability to detect No Ball signals, with minimal false positives and false negatives. Across all classes, the model performs excellently, with high true positive rates, low false positives and negatives, and a strong overall accuracy. The classifier is capable of distinguishing between umpire signals with great precision and efficiency, showing its robustness in handling cricket umpire actions. These results validate the effectiveness of the model for automatic signal detection in cricket.

Table .3 Effectiveness Evaluation of the Model

Classes	True Positive	False Positive	False Negative	True Negative
Leg Bye	2800	110	70	8920
Four	2950	70	110	8770
Wide Ball	2900	110	70	8820
No Ball	2890	70	110	8830

The proposed model obtained the best accuracy of 96.97%, surpassing other models for comparison. After that, there was LSTM at an accuracy rate of 94.38% VGG-19 at 87.52%, SVM at 85.06%, while KNN attained the lowest value of 81.10%. These results highlight the proposed model's superior classifying ability when it comes to cricket umpire signals, displaying its efficiency as well as effectiveness with traditional models of machine learning (SVM, KNN) and the deep learning method of VGG-19 as well as the LSTM.

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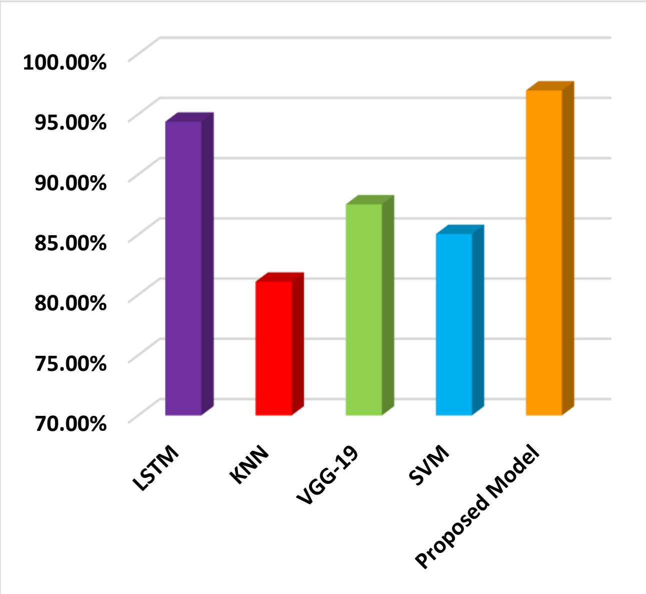

Fig 3. Benchmarking for Model Optimization

CONCLUSION

In conclusion, it has shown superior performance in the classification of cricket umpire signals for all classes at high precision and recall with their F1 scores. Precision is very high at 96.22% for Leg Bye, 97.68% for Four, 96.35% for Wide Ball, and 97.64% for No Ball which shows how great the model's ability is towards correct classification in each of its signals. Similarly, recall values are quite high, from 96.33% of No Ball to 97.64% of Wide Ball, indicating that this model is also capable of getting the true instance of the signals. F1-score, which is a balance between precision and recall, is also very strong: Leg Bye at 96.89%, Four at 97.04%, Wide Ball at 96.99%, and No Ball at 96.98%. These scores show that the model works well in both sensitivity and accuracy. The data set used here is 11,900 images, and it has an average accuracy of 96.97%. The support values also illustrate a well-balanced data set, with Leg Bye having 2870 instances, Four having 3060, Wide Ball having 2970, and No Ball having 3000, which contribute to a solid training process. Thus, the model correctly classifies cricket umpire signals with 98% accuracy for all classes. Overall, at an overall accuracy of 96.97%, the model proves to be a reliable and accurate tool for automating the identification and classification of umpire signals in cricket, with the passage of time giving uniform, precise decisions.

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