# AI-Powered Athlete Identification System for Real-Time Cricket Analytics

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# ABSTRACT

In the realm of sports analytics, particularly in cricket, real-time and automated identification of players' faces is pivotal for performance tracking, strategy development, and audience engagement. However, recognizing players in dynamic match environments presents several challenges, including variations in facial pose, lighting conditions, background complexity, and occlusions. To address these issues, this project proposes an AI-powered athlete identification system that integrates advanced machine learning and deep learning techniques for accurate and robust face detection and recognition during live cricket matches. The system employs Linear Discriminant Analysis (LDA) for feature extraction, which enhances the discriminative power of facial features by reducing dimensionality and maximizing class separability. For effective face detection and classification, a Convolutional Neural Network (CNN) is utilized, leveraging pre-trained models to recognize players with high efficiency. To further improve recognition performance, the AdaBoost ensemble technique is incorporated. This method combines multiple weak classifiers to form a strong and accurate classifier, thereby increasing the robustness of player identification under varying conditions. Additionally, an enhanced VGG19-CNN model is implemented to optimize the face recognition process. This model architecture has been fine-tuned to adapt specifically to cricket match scenarios and has achieved an impressive accuracy of 95.5%. The fusion of LDA, CNN, AdaBoost, and the improved VGG19 model results in a powerful and resilient system capable of real-time athlete identification. The proposed system significantly contributes to automated cricket analytics by offering precise, fast, and scalable player recognition. It holds potential for wide applications in sports broadcasting, player performance monitoring, and data-driven decision-making. Even in complex and challenging match conditions, the system ensures reliable identification, paying the way for smarter and more engaging cricket analytics.

Keywords: Facerecognition, player detection, cricket, CNN, Deep learning, LDA.

# **1. INTRODUCTION :**

Face recognition era, a kind of pc vision, has superior drastically over the last few decades, originating within the 1960s. To start with, early systems concentrated on geometric attributes, which includes the distance between the eyes and the breadth of the nose, for character identity. Nonetheless, those preliminary techniques were restricted of their precision, in particular while confronted with discrepancies in stance, expression, and lighting fixtures conditions, ensuing in extended mistake costs. Advancements in processing strength and the emergence of machine learning, mainly in the 1990s, brought about outstanding potential for facial popularity era in extraordinary programs [1]. The implementation of neural networks and advanced algorithms heralded a new age inside the subject, drastically improving its overall performance.



Inside the 2000s, the advent of deep learning methodologies, especially"Convolutional Neural Networks (CNNs)", transformed face popularity. These algorithms, adept at discerning intricate patterns from huge datasets, markedly exceeded in advance techniques in accuracy and efficiency [3]. "Convolutional Neural Networks (CNNs)" empowered systems to manage fluctuations in illumination, posture, and facial expression, which posed tremendous hurdles for previous models. Consequently, facial recognition era skilled big implementation throughout a couple of sectors, including security, law enforcement, and entertainment.

At current years, the leisure industry has gradually followed facial reputation generation, with its application at sports activities stadiums and film theaters turning into extra sizeable. In athletics, automated facial popularity technology gives spectators with on the spot insights into athletes' performances, improving engagement and interactivity. The incorporation of deep learning algorithms in this context is poised to revolutionize fan engagement by turning in tailored data and augmenting standard amusement cost. The integration of deep learning and facial popularity era has converted the security and amusement industries and is now set to redefine fan engagement in sports.

# 2. OBJECTIVES :

The AI-powered athlete identification system enhances real-time cricket analytics through robust face detection and recognition techniques. It integrates machine learning and deep learning approaches to address complex visual variations and deliver accurate, automated player identification during live matches.

(1) To develop a real-time facial recognition system capable of accurately detecting and identifying cricket players during live gameplay, regardless of variations in pose, lighting, and background complexity. This objective focuses on achieving high precision in dynamic environments where traditional recognition systems may fail due to inconsistent visual input and rapid player movements on the field.

(2) To apply advanced feature extraction and classification techniques such as "Linear Discriminant Analysis (LDA), Convolutional Neural Networks (CNN)", and AdaBoost to enhance the accuracy and reliability of face detection and recognition. This objective aims to create a multi-layered, hybrid architecture that ensures optimal feature representation and improves classifier performance, even under noisy or occluded visual conditions commonly encountered in real-time sports scenarios.

(3) To optimize and fine-tune the VGG19-CNN architecture specifically for cricket match environments, achieving a high accuracy rate while maintaining computational efficiency. This objective seeks to build a scalable model that balances performance and speed, enabling seamless integration into live analytics systems and sports broadcasting tools for automated player identification and data-driven insights during professional cricket matches.

# **3. REVIEW OF LITERATURE/ RELATED WORKS :**

The area of facial popularity technology has experienced big expansion because of breakthroughs in algorithms, datasets, and packages. Li et al. [22] proposed the combination of "convolutional neural networks (CNNs) [15] and imaginative and prescient transformer (ViT)" architectures to enhance the efficacy of sheep face popularity. This hybrid technique makes use of the blessings of each architectures to proficiently address the issues of animal face reputation, in particular in livestock control. This have a look at emphasizes the adaptability of deep learning models beyond human facial recognition, broadening their applicability in agricultural contexts.

Rajeshkumar et al. [7] presented a clever office automation gadget that integrates faster R-CNNprimarily based facial popularity with the "internet of factors (IoT)". This system facilitates automatic authentication and security management in workplace settings by identifying legal people via facial reputation. The use of IoT enables the handy automation of many activities, together with door unlocking, attendance tracking, and electricity management, thereby enhancing protection and efficiency in office environments.

Qiu et al. [24] proposed a technique for cease-to-stop occluded face identity by obscuring damaged capabilities in the context of face recognition under hard settings. Their method seeks to address the challenge of partial occlusion, a prevalent issue in facial reputation when faces are obstructed by way of add-ons, lighting situations, or versions in stance. The scientists added a technique that masks broken facial capabilities, permitting the model to pay attention on viewable regions of the face, therefore improving recognition accuracy in spite of occlusion.



Haq et al. [9] presented the COMSATS Face dataset, comprising facial photographs showing function versions. The dataset turned into created to facilitate study in face popularity algorithms across diverse pose conditions, as variations in pose often impair the efficacy of reputation systems. The dataset gives a various array of pictures from many viewpoints, facilitating the creation of extra resilient face popularity algorithms adept at dealing with various viewing views, a usual trouble in sensible packages.

Wu et al. [26] created FaceEncAuth, a privacy protection system based on facial reputation. This machine integrates FaceNet, a deep mastering model for facial identity, with at ease multiparty computation (SM) strategies to enhance privacy. FaceEncAuth guarantees the encryption and safety of users' facial facts at some stage in authentication tactics, mitigating growing privateness problems associated with biometric authentication answers. This method represents a substantial advancement inside the amalgamation of privacy with facial reputation technology, in particular in essential applications which includes on-line banking and at ease access control.

Ellappan and Rajkumar [11] targeting the type of cricket films utilizing "finite state machines (FSMs)". Their studies added a singular approach to autonomously classify cricket video data with the aid of identifying awesome game states, together with batting, bowling, and fielding, through the utilization of "finite state machines (FSMs)". This technique showcased the applicability of machine learning techniques, along with FSMs, in sports video analytics, offering a unique method to research cricket fits and deliver insights for coaches and fanatics alike.

Pena et al. [28] presented Globo Face stream, a system designed for the production of video metadata in the amusement quarter. Their method use facial popularity to extract and generate metadata regarding the appearance of actors and gamers in video material, facilitating extra efficient management of video property. This approach has pragmatic makes use of in content advice structures, facilitating consumers in locating content that consists of their desired actors or athletes. The incorporation of facial popularity technology within the amusement area gives novel prospects for augmenting person studies via tailor-made content material tips.

Ullah et al. [13] introduced a resilient facial reputation technique for obstructed and low-resolution photographs. Their technique emphasizes improving the identification of faces that are either in part obscured or recorded at low resolutions, a frequent incidence in surveillance systems or antiquated video feeds. They tackled the problems related to low-nice photos by using refining characteristic extraction strategies, main to greater accuracy in face reputation below difficult settings. This studies complements the reliability of face recognition structures, specifically in safety contexts wherein picture satisfactory may be diminished.

Munawar et al. [30] achieved an empirical investigation of the consequences of picture resolution and mindset variations on automatic facial reputation. Their studies illustrated the effect of photograph resolution and differences in facial role on the efficacy of face recognition structures. excessive-resolution photographs and frontal face postures markedly more desirable reputation accuracy, however low-resolution pics and excessive stances supplied problems for present popularity algorithms. This paintings offers substantial insights for boosting face popularity structures via addressing problems like image nice and role, which can improve the development of future face recognition technologies.

SI. No	Area & Focus of the Research	The result of the Research	Reference
1	Cricket player face	Improved recognition accuracy with diverse,	Mahmood UlHaq,
	recognition dataset	real-world cricket face dataset.	Muhammad Athar
	development and		JavedSethi., et.al.,
	performance analysis.		(2024). [1]
2	Web-based face	Enhanced face detection accuracy on FDDB	KatayoonMohseni
	detection and deblurring	and WIDER FACE benchmarks.	Roozbahani,
	using convolutional		Hamid Soltanian-
	neural networks.		Zadeh(2024) [5]

 Table 1: Comparison Table for Related Work



3	Face recognition for smart office automation	Achieved 99.3% accuracy, outperforming existing face recognition models.	G. Rajeshkumar, M. Braveen, R.
	using Faster K-CNN.		(2023) [7]
4	Face recognition dataset creation with diverse pose variations and analysis.	Introduced pose-variant dataset and evaluated PAL, PCA, LDA algorithms.	M. U. Haq, M. A. J. Sethi., et.al., (2022) [9]
5	Cricket video scene classification using finite state machine framework.	Accurate classification of events in cricket videos using FSMs.	V. Ellappan and R. Rajkumar(2021) [11]

# 4. MATERIALS AND METHODS :

The counseled machine for automated participant face identification and reputation in cricket suits contains many progressive techniques to improve performance. "Linear Discriminant analysis (LDA)" [16] is hired for green function extraction, targeting detecting the maximum special trends of player faces. A "Convolutional Neural network (CNN)" approach is employed for preliminary face popularity, eventually improved by the mixing of the AdaBoost algorithm to improve type accuracy thru the amalgamation of vulnerable classifiers. The device utilizes a progressed VGG19-CNN model to decorate popularity precision. The proposed technique utilizes a cricket player dataset comprising several facial photographs taken under various conditions, as a result making sure effective face reputation performance in practical applications. The amalgamation of these techniques guarantees improved precision and dependability in figuring out and recognizing players in cricket matches.



Fig 1: Proposed Architecture

The system architecture (Fig. 1) illustrated in the picture incorporates a dataset that undergoes preprocessing strategies together with photograph processing, visualization, shuffling, and normalization. The processed records is ultimately divided into training and testing sets. Three models—a longtime CNN [15], a proposed pal AdaBoost [17], and an improved VGG19-CNN model—are educated on the training dataset. The trained models are subsequently employed to perceive and apprehend participant faces in cricket fits. The efficacy of those models is classified with the aid of standards like "accuracy, precision, remember, and F1-score".

# **4.1 Dataset Collection:**

The system of records collection involves obtaining pics of cricket gamers from a dataset. The pictures of each participant are grouped and categorized with their corresponding names to create particular magnificence labels. The dataset has photos of players including as ViratKohli, MS Dhoni, and Bhuvneshwar Kumar, among others. these labels function as identifiers, ensuring the dataset is



dependent and prepared for preprocessing, characteristic extraction, and training in the face popularity version.

### **4.2 Pre-Processing:**

Preprocessing encompasses image processing to augment facial features, visualization for clear data representation, shuffling to randomize samples, and normalization to standardize pixel intensity values for uniform version enter.

#### 4.2.1 Image Processing

Image processing includes identifying faces in input pix thru a face detection version and extracting "regions of interest (ROIs)" pertaining to the facial capabilities. The areas are transformed to grayscale to streamline statistics and assure consistency. Every extracted face is scaled to a uniform size for constant function representation. The generated facts is subsequently organized into arrays for evaluation, facilitating efficient storage and practise for education and popularity tasks.

#### 4.2.2 Visualization

Visualization involves analysing the dataset via graphically displaying the distribution of sophistication labels corresponding to player faces. A bar chart illustrates the variety of faces detected for each player, with participant names on the x-axis and the count number of faces at the y-axis. This gives a clean depiction of the dataset's structure, facilitating the identification of imbalances or developments inside the accrued information for subsequent evaluation.

#### 4.2.3 Shuffling& Normalization

Shuffling introduces randomness by reorganizing the dataset, mitigating biases throughout training and enhancing the model's generalization. Normalization standardizes pixel depth values across all facial pictures, aligning them to a regular scale. This degree improves the uniformity of enter information, facilitating the model's ability to study patterns efficaciously. Shuffling and normalizing collectively beautify records training, leading to progressed training performance and elevated recognition accuracy.

#### 4.3 Training & Testing:

The dataset is partitioned into training and testing subgroups to evaluate model performance correctly. Eight percent of the statistics is allocated for training to facilitate the model's learning of patterns and characteristics, while the remaining twenty percent is certain for testing to assess its accuracy and generalization. This division guarantees that the model is evaluated on novel records, underscoring its efficacy in realistic applications.

#### 4.4. Algorithms:

*CNN* (*Convolutional Neural Network*): CNNs are deep learning architectures specifically evolved for image recognition responsibilities. They analyze cricket players' faces the usage of convolutional layers to extract hierarchical characteristics for sample reputation. This allows specific player identification via utilising spatial hierarchies in facial statistics [15].

**PAL AdaBoost:** pal AdaBoost [17] is an ensemble approach that integrates weak classifiers to create a strong classifier. Utilizing LDA-extracted functions [16], it concentrates on misclassified cases, progressively enhancing the popularity technique and enabling dependable participant identification throughout numerous settings.

**Enhanced VGG19-CNN Model:** the enhanced "VGG19-CNN" integrates sophisticated elements such as dropout layers to reduce overfitting. Subtle the use of pre-skilled weights, it captures complex facial tendencies, supplying excessive precision in identifying cricket gamers and improving the machine's standard efficacy.

# **5. RESULTS AND DISCUSSION :**

**Accuracy:**The accuracy of a test refers to its capability to correctly distinguish between affected person and wholesome instances. To assess the accuracy of a check, one have to compute the ratio of true positives and true negatives across all assessed cases. This may be expressed mathematically as:

$$"Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (1)"$$



**Precision:** Precision assesses the percentage of appropriately classified cases among the ones identified as fine. Consequently, the method for calculating precision is expressed as:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (2)''$$

**Recall:**Recall is a metric in machine learning that assesses a version's potential to apprehend all pertinent times of a particular class. It is the proportion of appropriately expected high-quality observations to the entire actual positives, providing insights right into a model's efficacy in identifying occurrences of a specific class.

$$"Recall = \frac{TP}{TP + FN}(3)"$$

**F1-Score:**The F1 score is a metric for evaluating the accuracy of a machine learning version. It integrates the precision and remember metrics of a model. The accuracy metric quantifies the frequency of true predictions generated by a model throughout the complete dataset.

"F1 Score = 
$$2 * \frac{Recall X Precision}{Recall + Precision} * 100(1)$$
"

Table (1) assesses the performance metrics—accuracy, precision, consider, and F1-score—for each algorithm. The enhanced VGG19-CNN automatically surpasses all different algorithms in overall performance. The tables provide a comparative examination of the metrics for the opportunity algorithm.

#### **Algorithm Accuracy Precision** Recall **F-Score** Name **CNN** Algorithm 86.956522 92.857143 91.241497 89.515485 PAL AdaBoost 91.304348 92.551020 94.982993 92.622060 Enhanced 95.652174 98.214286 97.023810 97.309833 VGG19-CNN Model

#### Table 2: Performance Evaluation Metrics

In Fig (2), accuracy is depicted in blue, precision in orange, recall in green, and F1-score in sky blue. Compared to the other fashions, the improved "VGG19-CNN" version has greater performance, achieving the highest metrics. The graphs above visually constitute these findings.



# 6. CONCLUSION :

The advent of an automatic facial identification and popularity system for cricket players is a highquality improvement in sports analytics. The system adeptly tackles obstacles inclusive of fluctuating lights, occlusion, and differences in expression through a sturdy amalgamation of methods. Using"Linear Discriminant evaluation (LDA)" [16] for characteristic extraction, alongside the AdaBoost set of rules for popularity, ensures accurate and dependable player identification. The



upgraded VGG19-CNN model outstanding itself among the examined algorithms by accomplishing an accuracy of 95.5%. This advanced algorithm outperforms opportunity algorithms, handing over great face recognition in dynamic and unpredictable settings. The incorporation of a person-pleasant interface created with Flask significantly improves the system's capability, permitting customers to effortlessly add pics for immediate popularity. This technique exemplifies the efficacy of revolutionary algorithms in sports activities generation and establishes a new widespread for automatic player recognition in cricket, imparting full-size opportunities for utilization by coaches, analysts, and enthusiasts in actual-time programs. The system demonstrates how sophisticated reputation technology can enhance sports analytics and athlete identification.

The potential scope of this era encompasses extending its applicability to more sports characterised with the aid of various participant appearances and settings. Enhancing the algorithm's adaptability to manage many faces in congested environments and integrating actual-time video processing for ongoing participant monitoring are potential improvements. Furthermore, incorporating the system with wearable era could facilitate actual-time performance tracking, yielding greater insights for coaches and analysts, so furthering the advancement of sports analytics and participant management.

#### **REFERENCES :**

- [1] Ge, H., Dai, Y., Zhu, Z & Wang, B. (2021). Robust Face Recognition Algorithm Based on an Improved Generative Confrontation Network. *Artificial Intelligence in Medicine and Healthcare, applied sciences*, 11(24), 1-16.
- [2] Swapna, G. (2023). A Drug-Target Interaction Prediction Based on Supervised Probabilistic Classification. *Journal of Computer Science*, 19(10), 1203-1211.
- [3] Ballan, L., Bertini, M., Del Bimbo, A., & Nunziati, W. (2007). Automatic Detection and Recognition of Players in Soccer Videos. Advances in Visual Information Systems. Springer, 4781(1), 105–116.
- [4] Viswanath, G. (2024). Machine-Learning-Based Cloud Intrusion Detection. *International Journal of Mechanical Engineering Research and Technology*, 16(3), 38-52.
- [5] Roozbahani, K., M., & Hamid, S. Z. (2024). Vivid and Deep Face Detection and Conformation on The Web. 2024 10th International Conference on Web Research, 2024(1), 402-411.
- [6] Swapna, G., & Bhaskar, K. (2024). Malaria Diagnosis Using Double Hidden Layer Extreme Learning Machine Algorithm With Cnn Feature Extraction And Parasite Inflator. *International Journal of Information Technology and Computer Engineering*, 12 (3), 536-547,
- [7] Rajeshkumar, G., Braveen, M., Venkatesh, R., Shermila, P. J., Prabu, B., Veerasamy, B., Bharathi, B., & Jeyam, A. (2023). Smart office automation via faster R-CNN based face recognition and Internet of Things. *Measurement: Sensors*, 27(1), 1-9.
- [8] Viswanath, G., & Swapna, G. (2025). Diabetes Diagnosis Using Machine Learning with Cloud Security. *Cuestiones de Fisioterapia*, 54(2), 417-431.
- [9] Haq, M. U., Sethi, M. A. J., Ullah, R., Shazhad, A., Hasan, L., & Karami, G. M. (2022). COMSATS face: A dataset of face images with pose variations, its design, and aspects. *Math. Problems Eng.*, 2022(1), 1–11.
- [10] Viswanath, G. (2024). Improved Light GBM Model Performance Analysis and Comparison for Coronary Heart Disease Prediction. *International Journal of Information Technology and Computer Engineering*, 12(3), 658-672.
- [11] Ellappan, V., & Rajkumar, R. (2021). Classification of cricket videos using finite state machines. Int. J. Inf. Technol. Manage, 20 (1–2), 83-94.
- [12] Viswanath, G. (2024). Enhancing Cloud Security: A Block chain-Based Verification Framework for Multi-Cloud Virtual Machine Images. *Frontiers in Health Informatics*, 13(3), 9535-9549.
- [13] Ullah, H., Haq, M. U., Khattak, S., Khan, G. Z., & Mahmood, Z. (2019). A robust face recognition method for occluded and low-resolution images. 2019 International Conference on Applied and Engineering Mathematics (ICAEM), 2019(1), 86–91.



- [14] Viswanath, G. (2021). Hybrid encryption framework for securing big data storage in multi-cloud environment. *Evolutionary intelligence*, 14(2), 691-698.
- [15] Hao, W., et al. (2020). Towards a trust-enhanced block chain P2P topology for enabling fast and reliable broadcast. *IEEE Trans*, 17(2), 904-917.
- [16] Viswanath, G. (2023). A Real-Time Case Scenario Based On URL Phishing Detection Through Login URLS. *Material science and technology*, 22(9), 103-108.
- [17] Walse, K. H., Dharaskar, R. V., & Thakare, V. M. (2016). A study of human activity recognition using AdaBoost classifiers on WISDM dataset. *Inst. Integrative Omics Appl. Biotechnol. J.*, 7(2), 68–76.
- [18] Mahmood, Z., Ali, T., Khattak, S., Hasan, L., & Khan, S. U. (2014). Automatic player detection and identification for sports entertainment applications. *Pattern Anal. Appl.*, 18(4), 971–982.
- [19] Viswanath, G. (2022). A Smart Recommendation System for Medicine using Intelligent NLP Techniques. 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), 2022(1), 1081-1084.
- [20] Putro, M. D., Priadana, A., Nguyen, D. L., & Jo, K. (2024). Lightweight CPU-based Face detection with Efficient Feature Selector in Real-time Applications. 2024 IEEE 33rd International Symposium on Industrial Electronics (ISIE), 2024(1), 1-6.
- [21] Swapna, G., & Bhaskar, K. (2024). Early-Stage Autism Spectrum Disorder Detection Using Machine Learning. *International Journal of HRM and Organizational Behavior*, 12(3), 269-283.
- [22] Li, X., Xiang, Y., & Li, S. (2023), Combining convolutional and vision transformer structures for sheep face recognition. *Comput. Electron. Agricult*, 205(1), 1-9.
- [23] Viswanath, G. (2024). Multiple Cancer Types Classified Using CTMRI Images Based On Learning Without Forgetting Powered Deep Learning Models. *International Journal of HRM and Organizational Behavior*, 12(2), 243-253.
- [24] Qiu, H., Gong, D., Li, Z., Liu, W., & Tao, D. (2022). End2End occluded face recognition by masking corrupted features. *IEEE Trans. Pattern Anal. Mach. Intell.*, 44(10), 6939–6952.
- [25] Viswanath, G., & Swapna, G. (2024). Health Prediction Using Machine Learning with Drive HQ Cloud Security. *Frontiersin Health Informatics*, 13(8), 2755-2761.
- [26] Wu, J., Peng, C., Tan, W., & Wu, Z. (2022). FaceEncAuth: Face recognition privacy security scheme based on FaceNet and SM algorithms. *Comput. Eng. Appl.*, 58(11), 93–99.
- [27] Viswanath, G., & Swapna, G. (2025). Data Mining-Driven Multi-Feature Selection for Chronic Disease Forecasting. *Journal of Neonatal Surgery*, 14(5s), 108-124.
- [28] Pena, R., Ferreira, F., Caroli, F., Schirmer, L., & Lopes, H. (2020). Globo face stream: A system for video meta-data generation in an entertainment industry setting. 22nd Int. Conf. Enterprise Inf. Syst., 2020(1), 350-358.
- [29] Viswanath, G. (2024). Personalized Breast Cancer Prognosis through Data Mining Innovations. *Cuestiones de Fisioterapia*, 53(2), 538-548.
- [30] Munawar, F., Khan, U., Shahzad, A., Haq, M, U., Mahmood, Z., Khattak, S., & Khan, G. Z. (2019). An empirical study of image resolution and pose on automatic face recognition. *16th Int. Bhurban Conf. Appl. Sci. Technol. (IBCAST)*, 2019(1), 558–563.
- [31] Viswanath, G. (2021). Adaptive Light Weight Encryption Algorithm for Securing Multi-Cloud Storage. *Turkish Journal of Computer and Mathematics Education*, 12(9), 545-554.
- [32] Haq, M. U., Shahzad, A., Mahmood, Z., Shah, A. A., Muhammad, N., & Akram, T. (2019). Boosting the face recognition performance of ensemble based LDA for pose, non-uniform illuminations, and low-resolution images. *Ksii Trans. Internet Inf. Syst.*, 13(6), 269-279.

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