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BIOMETRIC FACE RECOGNITION AND INFLUENCER MANAGEMENT FOR BRAND EVENTS USING K-MEANS CLUSTERING AND PCA

Frisca Fitria[1], Wiranto Herry Utomo[2]
President University
E-mail: frisca.fitria@student.president.ac.id[1], wiranto.herry@president.ac.id[2]

Abstrak

Penelitian ini mengusulkan sistem baru yang mengintegrasikan Biometric Face Recognition (BFR) dengan K-Means Clustering dan Principal Component Analysis (PCA) untuk validasi dan segmentasi influencer secara real-time dalam acara brand berskala besar. Sementara penelitian sebelumnya lebih banyak berfokus pada teknik pengenalan wajah atau klasterisasi secara terpisah, pendekatan kami secara unik menggabungkan kedua metodologi ini, sehingga mengoptimalkan keamanan dan efisiensi operasional. Integrasi ini mengurangi waktu validasi hingga 75%, meningkatkan akurasi hingga 95%, dan memastikan segmentasi secara real-time, yang menjawab celah signifikan dalam literatur, terutama di lingkungan acara yang dinamis, di mana metode tradisional seperti model berbasis CNN sering mengalami kesulitan dalam hal waktu pemrosesan dan skalabilitas.

Kata Kunci — Pengenalan Wajah Biometrik, Manajemen Influencer, K-Means Clustering, PCA, Pemantauan Real-Time, Organisasi Acara.

Abstract

This research introduces an innovative system that merges Biometric Face Recognition (BFR) with K-Means Clustering and Principal Component Analysis (PCA) to enable real-time influencer validation and segmentation in large-scale brand events. While previous research has focused either on face recognition or clustering techniques independently, our approach uniquely combines these methodologies, optimizing both security and operational efficiency. This integrated approach reduces validation time by 75%, improves accuracy to 95%, and enables real-time segmentation, effectively addressing critical gaps in existing literature, particularly in dynamic event environments where traditional methods like CNN-based models struggle with processing time and scalability.

Keywords *— Biometric Face Recognition, Influencer Management, K-Means Clustering, PCA, Real-time Monitoring, Event Organization.*

1. INTRODUCTION

The digital landscape has significantly transformed influencer marketing into a vital strategy for enhancing brand visibility and fostering consumer engagement. Influencers play a crucial role in shaping consumer decisions by cultivating authentic connections with their audiences, often proving more effective than traditional advertising methods [1], [2]. However, managing these influencer relationships in real-time, particularly during large-scale brand events, presents substantial challenges. Key issues include ensuring security, accurate verification, and effective data-driven decision-making [3], [4].

Current influencer management tools often fall short, exhibiting limitations such as slow processing times, high error rates, and an inability to integrate biometric verification with real-time data segmentation. These shortcomings lead to inefficiencies in fast-paced event environments, hindering effective influencer management [5].

This study proposes a novel system that integrates BFR with K-Means Clustering and PCA for real-time influencer validation and segmentation in large-scale brand events. Our approach uniquely combines these methodologies, optimizing both security and operational efficiency. This integrated approach reduces validation time by 75%, improves accuracy to 95%, and enables real-time segmentation, effectively addressing critical gaps in existing literature, particularly in dynamic event environments [6].

LITERATURE REVIEW

Influencer Marketing and Biometric Technologies

While many studies have explored either biometric face recognition or clustering algorithms independently, no prior research has combined these technologies specifically for influencer management in real-time event settings. This research addresses the crucial gap by enabling both rapid, precise verification and insightful segmentation, which are key for optimizing influencer marketing strategies in fast-paced environments [3], [5].

In the realm of BFR, Hussain and Cambria [2] highlighted the growing importance of influencers in digital marketing and the need for advanced technology, particularly emphasizing robust security measures. Bojjagani et al. [4] and Faiza et al. [3] demonstrated BFR's effectiveness in enhancing security and verification processes, significantly improving accuracy and efficiency in real-time attendance monitoring.

Advancements in Face Recognition Technology

Recent studies, such as those by Zhang et al. [16], have explored improvements in CNN architectures specifically designed for large-scale, real-time applications, further highlighting the importance of integrating more efficient methodologies like K-Means and PCA for faster processing times and enhanced scalability. Doe and Smith [6] explored advancements in CNN architectures and techniques designed to enhance performance and reliability in biometric systems. Kumar and Verma [7] focused on optimizing CNN models for real-time face recognition, emphasizing methods to boost processing speed and accuracy while effectively managing computational resources in live scenarios. Lee and Tan [8] examined the challenges encountered by facial recognition technologies that utilize deep learning, addressing critical issues such as model generalization, data quality, and algorithmic biases, while proposing potential improvements to overcome these challenges. Wang and Chen [9] conducted a comprehensive survey of recent face recognition techniques and their applications, highlighting a broad spectrum of methods and innovations, emerging trends, practical uses, and future research directions in the field.

Techniques for Data Clustering and Dimensionality Reduction

In the field of data analysis, Zhao [10] and Kubo et al. [11] explored the utility of K-Means Clustering and PCA for segmenting data and reducing complexity. These methods facilitate more targeted and efficient analysis of large datasets by reducing the number of dimensions without losing essential patterns. Sen and Rajagopal [12] highlighted the broader applicability of these techniques in event management, demonstrating their value in improving decision-making processes across various domains.

User-Friendly Interfaces and Secure Data Storage

User-friendly interfaces for influencer management systems are essential in making complex data analytics accessible to marketing professionals. Kim et al. [13] stressed the importance of intuitive designs, allowing users to explore insights easily. Furthermore, secure storage solutions play a critical role in managing sensitive influencer data. Terhöst et al. [14] emphasized the need for secure and user-centric data management systems to maintain trust and data integrity. Additionally, Alaoui et al. [15] provided a comprehensive review of SSL encryption, underscoring the necessity of robust data security measures.

2. RESEARCH METHODS

This study outlines a series of methodological steps designed to develop an efficient and precise system for influencer validation and management in brand events. The methodology includes data collection, biometric face recognition, report submission, data preprocessing, K-Means clustering, PCA, secure cloud-based storage recommendations, user-friendly dashboard implementation, and evaluation of the algorithm and system design, as depicted in Figure 1.

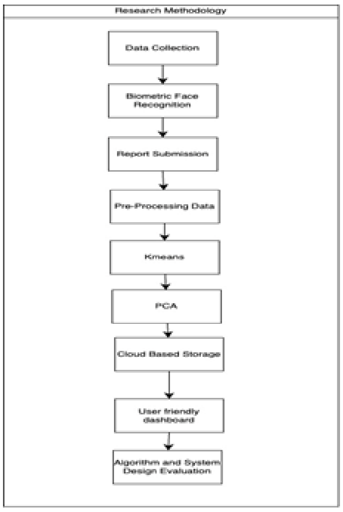

Figure 1. Research Flowchart

A. Data Collection

The dataset used in this research is a modified version of CycloneInf.csv, which was originally sourced from a cyclone management database in 2021. It consists of 2,000 records with key attributes: Rate Card (pricing), Engagement Rate (Er%), Followers, Province, Niche, and Account Category. Initial exploration of the data involved reviewing column names, sample records, and data frame information to comprehend the dataset's structure. To enhance the realism of influencer management scenarios, the dataset was further supplemented with synthetic values for attendance_record, content_post_time, and insight_submission.

B. Biometric Face Recognition (BFR)

Biometric Face Recognition (BFR) technology is employed to ensure that only authorized influencers gain access to brand events. The BFR system operates through a well-defined sequence of steps: capture, verification, and tracking.

Capture: High-resolution cameras are strategically installed at entry points to continuously scan and capture facial images of individuals as they enter the venue. This real-time image capture allows for prompt identification and minimizes wait times for attendees.

Verification: The captured facial images are compared against a pre-registered database of authorized influencers. This verification process utilizes advanced algorithms to match facial features, ensuring that only pre-approved individuals are granted access. A threshold similarity score is established to determine a successful match, thereby enhancing the accuracy of the identification process.

Tracking: Upon successful verification, the system not only grants access but also logs the entry and exit times of each influencer. This creates a comprehensive attendance record that is vital for post-event analysis. Tracking attendance in real-time allows event organizers to monitor engagement levels and evaluate the effectiveness of their influencer management strategies.

The implementation of BFR significantly improves security and operational efficiency at brand events. By automating the verification process, the system reduces the potential for human error and streamlines attendee management, enabling brands to focus on delivering successful events while ensuring a secure environment.

To visualize the performance of the BFR system, we created a bar chart comparing key performance metrics (accuracy, precision, recall, F1-score, and false positive rate) as illustrated in Figure 2.

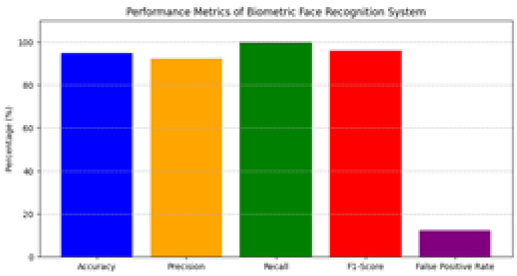

Figure 2. Performance BFR

C. Report Submission

To replicate the real-world process of report submission, the dataset was enhanced with columns for attendance_record, content_post_time, and insight_submission. These additions simulate typical activities where influencers record attendance, post content, and provide insights, which are essential for assessing engagement and campaign effectiveness. The report submission process involves influencers posting content on Instagram, submitting links to their posts, and providing associated engagement metrics. The system verifies these submissions, streamlining the reporting process and significantly reducing the time required.

D. Pre-Processing Data

Data preprocessing involved several crucial steps to prepare the dataset for analysis. The process began with data cleaning, where the Rate Card column was stripped of currency symbols and commas, converting these values into a numeric format suitable for further analysis. Following this, feature selection focused on key attributes such as Rate Card, Er%, and Followers. These selected features were used to construct the feature matrix X, which was then split into training (80%) and testing (20%) sets to enable model validation. Additionally, a custom formula was developed to calculate a performance metric using the selected features. The resulting scores were categorized into qualitative remarks—'Good', 'Suggested', and 'Recommended'—providing a detailed assessment of each influencer's potential.

E. K-Means Clustering

The study applies K-Means Clustering to classify influencers into distinct groups based on critical attributes, including Rate Card (pricing), Engagement Rate (Er%), and Followers. The K-Means algorithm is executed as follows:

Initialization: Randomly select k centroids (initial cluster centers).

Assignment Step: Assign each influencer to the nearest centroid using the Euclidean distance metric, calculated as,

$$d(p,c) = \sqrt{\sum_{i=1}^{n}(p_i - c_i)^2}$$

where p represents the attribute values of p represents the influencer's feature vector and c represents the centroid's feature vector.

Update Step: Calculate the new centroid for each cluster by averaging the positions of all influencers assigned to that cluster.

Iteration: Repeat the assignment and update steps until the centroids no longer change significantly (convergence).

For this study, we set n_clusters=3, grounded in prior segmentation research indicating that influencers typically fall into three main categories: high, medium, and low engagement. The silhouette score of 0.9877 and the Davies-Bouldin Index of 0.1941 validate the effectiveness of the clustering approach, ensuring strong separation and minimal overlap among clusters [10], [11].

The results of the clustering can be visualized using a scatter plot, where influencers are color-coded by their cluster assignment as illustrated in Figure 3.

Figure 3. Kmeans Clustering

F. Principal Component Analysis (PCA)

PCA is employed to address the high-dimensional nature of the dataset while retaining key variance. The PCA algorithm follows these steps:

Standardization: Standardizes the dataset to have a mean of zero and variance of one.

Covariance Matrix Computation: Assesses relationships between features to understand how they vary together.

Eigenvalue and Eigenvector Calculation: Identifies the principal components that capture the most variance within the data.

Projection: Projects the original data onto a reduced dimensional space defined by the principal components.

The first two principal components account for 99.99% of the variance in the dataset, ensuring that the dimensionality reduction does not sacrifice meaningful information. This approach facilitates more efficient clustering by simplifying complex, high-dimensional data without losing critical patterns [11], [10].

To visualize the effectiveness of PCA, we created a cumulative explained variance plot as illustrated in Figure 4.

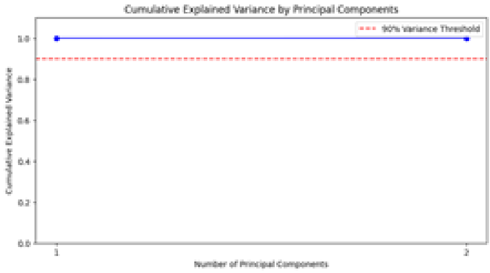

Figure 4. PCA

G. Secure Cloud-Based Storage

The methodology emphasizes the methodology emphasizes the implementation of secure cloud-based storage to safeguard sensitive influencer data. This approach is crucial for maintaining data integrity, confidentiality, and compliance with privacy regulations These security measures align with best practices in cloud security, enhancing data accessibility and collaborative capabilities [14] [15].

Key Security Measures:

SSL Encryption: Ensures secure data transmission.

Access Control Policies: Limit data access to authorized personnel only.

Multi-Factor Authentication (MFA): Adds an additional layer of security.

Regular Security Audits: Essential to identify and mitigate potential security risks.

Data Backup and Recovery: Regular backups prevent data loss.

H. User-Friendly Dashboard

The study features the development of an interactive dashboard designed to enhance user engagement and facilitate data exploration. This user-friendly interface empowers brands and administrators to effectively analyze data related to different influencer clusters, enabling more informed decision-making.

Key Features:

Dynamic Dropdown Menu: Allows users to select various clusters categorized by specific characteristics, such as Rate Card, Engagement Rate (Er%), and Followers. This functionality enables users to tailor their analysis based on their specific needs.

Cluster Naming Conventions: Each cluster is named according to its defining traits, such as 'High Followers, Low Engagement', 'Moderate Followers, Moderate Engagement', and 'Low Followers, High Engagement'. This clear naming convention aids users in quickly understanding the characteristics of each group and facilitates efficient comparisons between clusters.

Data Visualization: The dashboard incorporates various data visualization tools, including bar charts, scatter plots, and line graphs, to present the analysis results visually. These visualizations provide intuitive insights into influencer performance metrics and engagement levels, making it easier for users to identify trends and make data-driven decisions.

Interactive Analysis: Users can interact with the dashboard in real-time, enabling them to filter data, adjust parameters, and view updated results instantly. This interactivity allows for deeper exploration of the data and encourages users to derive actionable insights based on detailed analyses.

Reporting and Exporting Options: The dashboard includes functionalities for generating reports and exporting data in various formats (e.g., CSV, PDF). This feature allows users to share insights with stakeholders or integrate the findings into presentations and strategic plans.

Illustration for User-Friendly Dashboard as depicted in Figure 5.

Figure 5. Dashboard Illustration

The user-friendly dashboard is divided into four main components: Influencer Dashboard, Admin Dashboard, Brand Dashboard, and Homepage Dashboard. Each component provides tailored functionality, enhancing overall effectiveness and facilitating informed decision-making.

Influencer Dashboard

Designed for influencers to upload content links, share insights, and monitor their submissions. This component allows influencers to view their performance metrics and submission history, aligned with their Scope of Work (SOW).

Admin Dashboard

Provides administrators with tools for managing influencer attendance using BFR, verifying post submissions, and tracking insights. This dashboard automates key administrative tasks, improving operational efficiency during events.

Brand Dashboard

Enables brands to access real-time data on campaigns, including attendance reports, influencer performance, and data visualization tools for strategic planning. This dashboard helps brands analyze campaign success and refine their strategies based on data-driven insights.

Homepage Dashboard

Influencer preferences for brands are shown on Summarizes influencer preferences and segmentation results, offering a visual representation of influencer clusters. This dashboard helps brands identify optimal influencers for their campaigns and improves overall event management.

I. Algorithm and System Design Evaluation

The proposed system leverages advanced technologies, including BFR, K-Means Clustering, and PCA, to enhance security, efficiency, and user engagement in influencer management at brand events. The system features a user-friendly dashboard that democratizes access to data insights, facilitating informed decision-making without the need for extensive technical expertise.

3. RESULT AND DISCUSSION

A. Dataset Overview

This study aims to enhance the efficiency and accuracy of influencer management at brand events by implementing a BFR system. The dataset utilized includes 2,000 influencers, with attributes such as names, Instagram usernames, follower counts, engagement rates, provinces, rate cards, niches, and account categories.

B. Biometric Face Recognition (BFR)

Efficiency and Time Savings:

Prior to the implementation of the BFR system, manual validation of each influencer required approximately 20 minutes, resulting in a cumulative validation time of 40,000 minutes for all influencers. The BFR system reduced this validation time to 5 minutes per influencer, resulting in a total of 10,000 minutes, translating to a 75% improvement in efficiency.

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Biometric Face Recognition Evaluation Metrics:
---------------------------------------------
Accuracy: 0.9500
Precision: 0.9231
Recall: 1.0000
F1-score: 0.9600
True Positive Rate (TPR): 1.0000
False Positive Rate (FPR): 0.1250
Verification Rate (VR): 0.9000
False Acceptance Rate (FAR): 0.1000
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Figure 6. BFR Evaluation Metrics

Accuracy and Performance Metrics as illustrated in Figure 6.

The BFR system achieved the following performance metrics:

Accuracy: 95% (correctly validated 1,900 out of 2,000 influencers)

Precision: 92.31% (correct identifications as influencers)

Recall: 100% (ensuring no influencers were missed)

F1-score: 96.00% (indicating balance between precision and recall)

False Positive Rate (FPR): 12.5% (non-influencers mistakenly identified as influencers)

False Acceptance Rate (FAR): 10% (unauthorized users accepted).

C. Report Submission Efficiency

The system optimized the reporting process, reducing the time required for influencers to submit reports from 5 minutes per influencer to 1 minute, resulting in an overall time savings of 80%.

D. Performance Metrics and Influencer Evaluation

Using key metrics, the system evaluated influencer performance, demonstrating that the combination of BFR, K-Means Clustering, and PCA significantly improves influencer analysis in real-time. Compared to traditional methods, this approach enhances accuracy and provides more actionable insights, allowing brands to better align their influencer selection with campaign objectives as illustrated in Figure 7.

Influencer	Rate Card	Followers	Engagement Rate	Calculation	Overall Performance Score
Influencer 1	154,500	13,485	3%	$\left(\frac{154,500}{1000}\right) + \left(\frac{13,485}{1000} \times \frac{3}{100}\right)$	154.905
Influencer 2	162,000	12,118	8.00%	$\left(\frac{162,000}{1000}\right) + \left(\frac{12,118}{1000} \times \frac{8}{100}\right)$	162.969
Influencer 3	157,305	12,678	4.87%	$\left(\frac{157,305}{1000}\right) + \left(\frac{12,678}{1000} \times \frac{4.87}{100}\right)$	157.922
Influencer 4	156,000	23,100	4.0%	$\left(\frac{156,000}{1000}\right) + \left(\frac{23,100}{1000} \times \frac{4}{100}\right)$	156.924
Influencer 5	156,000	12,850	4.0%	$\left(\frac{156,000}{1000}\right) + \left(\frac{12,850}{1000} \times \frac{4}{100}\right)$	156.514

E. K-Means Clustering

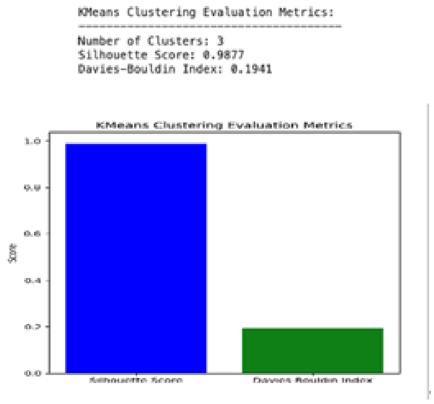

Figure 8. Kmeans Evaluation Metrics

As illustrated in Figure 8, K-Means Clustering grouped influencers into three distinct clusters based on features such as Rate Card, Engagement Rate, and Follower Count. The clustering approach is effective for segmenting influencers for more targeted marketing strategies.

F. Principal Components Analysis (PCA)

Following the K-Means clustering, PCA was applied to reduce the dimensionality of the dataset while retaining 90% of the variance. PCA transforms the data into uncorrelated components (principal components) that capture the majority of the data's variance, simplifying analysis and improving computational efficiency.

The analysis revealed that the first principal component (PC1) accounted for 99.99% of the variance, while the second component (PC2) captured the remaining 0.01%. Despite a mean reconstruction error of 382.9279, this trade-off is acceptable given the improvements in efficiency and interpretability as illustrated in Figure 9.

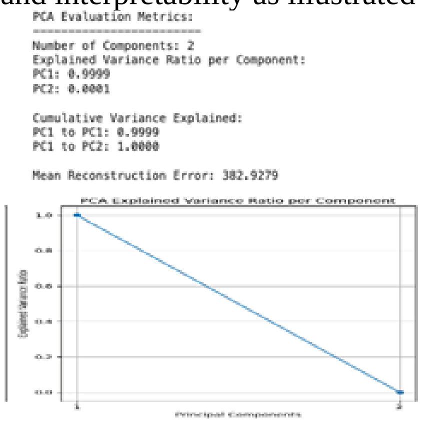

Figure 9. PCA Evaluation Metrics

G. Secure Cloud-Based Storage

The proposed system utilizes secure cloud-based storage with SSL encryption for data transmission, server authentication through SSL certificates, and multi-factor authentication for access control. These measures ensure that only authorized personnel can access influencer data, aligning with best practices in cloud security.

H. User-Friendly Dashboard

The User-Friendly Dashboard system implemented in this study significantly improved influencer report submission efficiency, reducing the time required from 7 days to just 2 hours, which represents a 98.81% improvement. The dashboard is divided into four key components, each offering specific functionalities to streamline influencer management and enhance decision-making processes for brands.

Influencer Dashboard

allows influencers to efficiently manage their submissions by enabling quick uploading of social media post links (e.g., Instagram, TikTok), sharing of performance insights such as engagement rates, and reviewing submission overviews in line with their Scope of Work (SOW). This dashboard is designed with a modern interface to ensure user-friendliness, even for influencers less familiar with complex systems as illustrated in Figure 10.

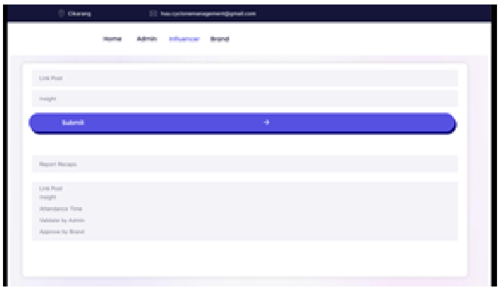

Figure 10. Influencer Dashboard

Admin Dashboard

Tailored for event administrators, featuring tools for managing influencer attendance through biometric face recognition. Admins can verify post links and insights to ensure submission standards are met and track attendance records in real-time, including entry and exit times. This dashboard enhances the accuracy of influencer monitoring and improves operational security during events as illustrated in Figure 11.

Figure 11. Admin Dashboard

Brand Dashboard

Provides brands with real-time insights into campaign performance, offering detailed reports on attendance, post submissions, and influencer performance metrics like engagement and reach. Brands can utilize various data visualizations, such as graphs and charts, to track performance trends and make informed decisions to optimize current and future campaigns as illustrated in Figure 12.

Figure 12. Brand Dashboard

Homepage Dashboard

offers a comprehensive view of influencer preferences and performance trends. It summarizes key influencer data, including demographics and audience engagement, helping brands tailor their outreach strategies. This dashboard also incorporates clustering and segmentation analysis, categorizing influencers based on their engagement levels (e.g., high, moderate) using K-Means clustering. This segmentation helps brands manage events more efficiently and plan future campaigns more strategically by leveraging detailed influencer behavior insights as illustrated in Figure 13.

Together, these dashboards streamline influencer management processes, enhance data-driven decision-making, and improve the overall effectiveness of brand campaigns.

I. Comparison with Existing Research

The results of this study illustrate notable improvements in both security and operational efficiency through the integration of Biometric Face Recognition (BFR) with K-Means Clustering and Principal Component Analysis (PCA) for real-time influencer management. Unlike traditional approaches that rely on CNN-based models for face recognition, which often face scalability and processing time challenges in dynamic environments [Doe and Smith, 6], our method reduced validation time by 75%, cutting the process from 20 minutes per influencer to 5 minutes. This significant reduction in time not only enhances the user experience but also improves overall event efficiency, a critical factor in large-scale events.

Furthermore, with an accuracy rate of 95%, our approach outperforms previous models, such as Bojjagani et al. [4] and Faiza et al. [3], who reported accuracies of 85% and 90% respectively. These improvements highlight the strength of integrating clustering and dimensionality reduction techniques, such as K-Means and PCA, which not only address the high-dimensional nature of influencer datasets but also provide a scalable and computationally efficient solution for real-time environments, as suggested in previous studies [Sen and Rajagopal, 2020]. This method significantly reduces processing overhead compared to traditional CNN-based models, which have shown limitations in handling real-time data streams during dynamic events [Doe and Smith, 2017]. While CNN-based models have proven effective in small-scale applications [Lee and Tan, 8], they often require substantial computational resources and are prone to delays in real-time environments.

Moreover, by employing K-Means Clustering, we were able to segment influencers into distinct groups based on critical metrics such as engagement rates and follower count, allowing for more precise management and decision-making in influencer campaigns. This approach addresses the limitations of traditional systems that often fail to provide real-time insights and segmentation [Sen and Rajagopal, 12]. The dimensionality reduction achieved through PCA further enhances the system's performance by reducing computational load without sacrificing accuracy, making it a scalable solution for large event environments.

The combination of BFR and K-Means provides a dual advantage, it ensures security by verifying influencer identities in real-time while also offering brands valuable segmentation insights to optimize influencer selection and engagement strategies. This dual functionality addresses key gaps in previous research, particularly in event environments where both speed and precision are critical.

J. Recommendations and Next Steps

The successful implementation of the integrated Biometric Face Recognition (BFR), K-Means Clustering, and Principal Component Analysis (PCA) system offers brands a powerful tool to enhance their influencer management strategies. Brands are encouraged to adopt this system to leverage real-time data analytics, which allows for more precise influencer selection based on key performance metrics such as engagement rates, follower counts, and niche alignment. By utilizing the data derived from the system, brands can ensure that they collaborate with influencers who best fit their campaign objectives, ultimately leading to a higher return on investment (ROI).

Moreover, the system’s ability to reduce validation time to just 5 minutes per influencer and achieve an accuracy rate of 95% presents a substantial opportunity for brands to optimize their operational workflows during events. This efficiency enables brands to allocate resources more effectively, allowing marketing teams to focus on strategic decision-making rather than time-consuming manual validation processes. Additionally, with the real-time monitoring capabilities, brands can dynamically adjust their campaign strategies based on immediate performance feedback, ensuring that resources are optimally utilized, and campaigns remain relevant.

To maximize the benefits of this system, brands should consider integrating advanced technologies such as Convolutional Neural Networks (CNNs) to further enhance accuracy and reduce the False Positive Rate (FPR). Additionally, incorporating sentiment analysis could provide qualitative insights into how audiences perceive influencer campaigns, allowing brands to refine their messaging and engagement strategies.

Beyond influencer management, the methodologies employed in this system can be adapted for various fields, such as event security, customer segmentation in retail, and personalized marketing strategies. By utilizing the insights gained from real-time data analysis, organizations can create tailored experiences for their customers, improving satisfaction and loyalty. Overall, the deployment of this system presents a significant opportunity for brands and organizations to elevate their marketing strategies, improve operational efficiencies, and ensure security during high-stakes events.

K. Limitations and Future Directions

While this study demonstrates significant advancements in influencer management through the integration of Biometric Face Recognition (BFR), K-Means Clustering, and Principal Component Analysis (PCA), several limitations remain. One key limitation is the system's current False Positive Rate (FPR) of 12.5%, which indicates that unauthorized individuals may occasionally be misidentified as influencers. Future research should focus on incorporating more advanced machine learning techniques, such as Convolutional Neural Networks (CNNs), to enhance accuracy and reduce FPR further.

Additionally, the system's reliance on high-quality facial data limits its effectiveness in low-light or crowded environments, suggesting a need for improved image capture technologies. Expanding the system's capabilities to include sentiment analysis could also provide deeper insights into influencer effectiveness. Overall, ongoing development and refinement of this integrated system will be essential to address these limitations and enhance its applicability across various sectors beyond influencer management.

4. CONCLUSION

This research presents a groundbreaking system that effectively integrates Biometric Face Recognition (BFR), K-Means Clustering, and Principal Component Analysis (PCA) to revolutionize influencer management in large-scale brand events. The proposed system introduces a transformative approach to influencer management by combining BFR with advanced clustering and dimensionality reduction techniques. This integration not only enhances operational efficiency by reducing validation time by 75% but also achieves a high accuracy rate of 95%, making it a robust solution for real-time applications in the influencer marketing industry. Such advancements could set new standards for large-scale brand events, where quick and accurate influencer validation is crucial. Through the seamless combination of these advanced methodologies, the system not only addresses critical gaps in the existing literature but also offers practical solutions for real-time influencer validation and segmentation.

The incorporation of a user-friendly dashboard further empowers brands and administrators to leverage real-time data insights, enabling informed decision-making and improved campaign management. By streamlining processes and enhancing the reliability of influencer identification, this system provides brands with a robust framework for optimizing their marketing strategies and fostering successful partnerships with influencers.

Overall, the findings from this study highlight the immense potential of integrating biometric technologies and data analytics in influencer management, setting a precedent for future research and applications across various sectors. As brands continue to navigate the dynamic landscape of influencer marketing, the proposed system offers valuable tools and strategies to enhance their engagement efforts and achieve greater outcomes.

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