Original Article

Foreground Detection in Dynamic Scenes using Singular Value Decomposition Algorithm in Comparison with Gaussian Mixture Model to measure F-score

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Abstract

Aim: The purpose of this work is to represent a foreground detection method using a novel Singular Value Decomposition (SVD) algorithm that gives improved accuracy and F-score. **Materials and Methods:** ClinCalc is a tool used tocompute sample sizesand displays the results of sample analyses. Cdnet 2014 dataset demonstrates our foreground detection using novel Singular value decomposition algorithm. Here Singular value decomposition is compared with the Gaussian mixture model(GMM). **Results:** Poor detection of moving objects is improved by using Singular value decomposition with mean F-score rate of 83% and accuracy of 87%. **Conclusion:** Singular value decomposition subtracts the background and detects the moving objects with better accuracy and F-score compared with GMM.

Keywords: Novel Singular Value Decomposition, GMM, Foreground Detection, Background subtraction, Accuracy, F-score.

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INTRODUCTION

The purpose of this study is background subtraction and to detect the foreground in dynamic scenes using Singular value decomposition (SVD) and to measure the F-score. The importance of this study is to improve video coding performance by integrating matrix decomposition and removing temporal, spatial, and statistical redundancies (Ho 2013). The process of separating the backdrop from a video is crucial for change detection. Because of the variance in illumination and the presence of noise, change detection approaches rely on fluctuations in intensity and texture in video processing (Singh 2009). The Neighbour-based Intensity Correction method identifies and adjusts the motion pixels based on the difference between the background and the current frame (Huynh-The et al. 2017). The background motion induced by orthographic cameras is found in a low rank subspace, and pixels corresponding to a single trajectory are found in a low rank subspace (Cui et al. 2012). This work has a wide range of applications, ranging from compression to scene interpretation for recognising moving objects in films captured by stationary cameras (Amintoosi, Farbiz, and Fathy 2007).

A lot of research has been done for foreground detection using the singular value decomposition algorithm. Total number of citations published was 21,243 from Google Scholar and 649 from Sciencedirect. The process of removing the smallest singular values from the saturation matrices allows us to retain more image quality (Cai 2018). The foreground detection of moving objects using a novel Singular value decomposition algorithm based on Cauchy statistical distribution (Zhang, Yao, and Liu 2008). Local SVD Binary Pattern to detect the potential structure of the local regions in an image to improve robustness (Guo, Xu, and Qiang 2016). The proposed technique gives the efficiency and color information of SVD to subtract background pixels and detect the foreground pixels (Jlassi, Douik, and Messaoud 2010). The background subtraction of SVD is shown in both qualitative and quantitative computations (Bouwmans, Aybat, and Zahzah 2016). Most of the foreground detection methods depend on intensity and texture variations of the image sequence (Haldrup 2014). A new method is developed to perform video reconstruction by low rank and sparse decomposition adaptively. Background subtraction becomes part of the reconstruction (Z. Wang, Fu, and Huang 2019). The dynamic mode decomposition technique integrates two of the leading data analysis methods such as novel singular value decomposition and fourier transforms (Erichson et al. 2019). Singular value decomposition algorithm uses linear algebra. SVD is used to reconstruct three-dimensional objects from a two-dimensional video or image sequence (Hallinan et al. 1999). A robust watermarking method is a combination of Tchebichef transformation and singular value decomposition. SVD is selected for watermark embedding to increase robustness (Richardson 2011).

Our institution is passionate about high quality evidence based research and has excelled in various fields (Parakh et al. 2020; Pham et al. 2021; Perumal, Antony, and Muthuramalingam 2021; Sathiyamoorthi et al. 2021; Devarajan et al. 2021; Dhanraj and Rajeshkumar 2021; Uganya, Radhika, and Vijayaraj 2021; Tesfaye Jule et al. 2021; Nandhini, Ezhilarasan, and Rajeshkumar 2020; Kamath et al. 2020). The major drawback of Gaussian mixture model (GMM) is less storage size and cost effectiveness. GMM cannot adjust internal sensitivity because of its low pixels. Mixture model doesn't consider semantic information. Because of variation in intensity of images, the output of the image sequence cannot be detected properly. The GMM method has low latency compared to SVD. While constructing three dimensional images from two-dimensional video streams, the objects can be missed and undetected. Due to high robustness, frames will disappear in few regions. To upgrade the texture of images in the proposed framework, programmatic coding experiences are done to check the presentation of the proposed approach. The main aim is to achieve an improvement in accuracy and F score and compare the novel singular value decomposition with GMM.

MATERIALS AND METHODS

This entire work is done in the Department of Electronics and Communication Engineering at Saveetha School of Engineering, SIMATS, Tamil Nadu, India. MATLAB software was used for the simulation of foreground detection in dynamic scenes. ClinCalc is a tool used to compute sample size of two groups (Charan et al. 2021). Each dataset consists of 10 samples which in total gives 20 samples. Cdnet 2014 dataset demonstrates the foreground detection in dynamic scenes using Singular value decomposition algorithm (SVD) in comparison with the Gaussian Mixture Model (Y. Wang et al. 2014). Pretest power is determined to be 80% with an error rate of 0.05.

For Group-1, the sample preparation for novel Singular value decomposition has been taken from a kaggle dataset extracted from Cdnet2014. Singular Value Decomposition (SVD) is the process of breaking down a matrix A into the form.

$$A=U \sum V^T \quad (1)$$

where U is a m*m is an orthonormal matrix, ∑ is an m*n matrix with singular values on the main diagonal and V is a n*an orthonormal matrix with columns. This algorithm allows us to keep the image's significant unique values while releasing the values that aren't as important to maintaining the image's quality. The supplied digital image is refactored into three matrices by SVD. Singular values are used to restructure the image, and the image is represented with a smaller set of values at the end of the process, resulting in a reduction in the amount of storage space required by the image.

For Group-2, the sample preparation for the Gaussian mixture model has been taken from a kaggle dataset extracted from Cdnet2014. GMM detects objects from the video images, the remaining pixels can then be connected into groups to represent foreground objects. In GMM every pixel is divided by its intensity in RGS color space. Every pixel is computed for its probability. Every pixel is computed for its probability. Gaussian Mixture is a function that has the same number of Gaussians as the entire number of clusters. Each Gaussian in the mixture has a set of parameters, which are as follows: The center is defined by a mean,the width is defined by the covariance and the probability.

$$p(X) = \Sigma K_{k=1} \Pi_k G(X|\mu_k,\Sigma_k) \qquad (2)$$

For the system setting, Windows-10 HP, Intel Core i5, 10th generation was used to do the simulation of novel Singular Value Decomposition algorithm (SVD) in comparison with the Guassian mixture model (GMM). The statistical software used was Matlab and SPSS analysis. MATLAB includes computation, algorithm development and simulation. SPSS is used to compare the proposed and existing algorithm.

Statistical Analysis
SPSS version 21 was used for statistical analysis of collected data for parameters by gain in dB and frequency in GHz (Gogoi* et al. 2020). The dependent variables of the background subtraction in detecting the foreground are precision, accuracy, F-score and recall. The independent variables of the foreground detection are TrueNegatives(TN), TruePositives(TP), FalseNegatives(FN), FalsePositives(FP). F-score and accuracy are calculated for comparing the two groups.

Precision = TruePositives / (TruePositives + FalsePositives)
Recall = TruePositives / (TruePositives + FalseNegatives)
F-Measure = (2 * Precision * Recall) / (Precision + Recall)
Accuracy = (TN+TP) / (TN+FP+TP+FN)

RESULTS

The accuracy and F-Score of the proposed Singular value decomposition algorithm (SVD) was compared with the existing algorithm Gaussian mixture model (GMM). The problems faced in detecting the objects in foreground are rectified by using the novel Singular value decomposition algorithm. Figure 1 shows the images extracted from Cdnet2014 dataset which are represented as inputs for this study. Figure 2 represents the output images of proposed algorithm SVD obtained by using MATLAB. Figure 3 represents the output images of the existing algorithm GMM extracted by using MATLAB. Table-1 compares the F-score obtained for sample 10 images of Singular value decomposition algorithm and Gaussian Mixture model where the mean Fscore rate of SVD is 83% and GMM is 79%. Table-2 compares the accuracy obtained for sample 10 images of Singular value decomposition and Gaussian Mixture model where the mean accuracy rate of SVD is 87% and GMM is 85%. In table-3 and table-4 the descriptive and group statistics of SVD and GMM are analyzed using SPSS where the mean (0.823550), standard deviation (0.0090996) and standard mean error rate (0.0028775) of SVD and the mean (0.801400), standard deviation (0.0110478) and standard mean error rate (0.0034936) of GMM. Table 5 represents the statistical analysis of independent sample tests for both the sample groups with significance $p < .001$, 95% confidence interval difference, the mean difference (.0221500, .0221500, .0262900, .0262900) and standard error difference (.0045261, .0045261, .0015614, .0015614) is obtained. Figure 4 represents the F-score graph between SVD and GMM. Figure 5 represents the accuracy graph between SVD and GMM using MATLAB. Figure 6 and Figure 7 represent the SPSS comparison graph between SVD and GMM.

DISCUSSION

Poor detection of moving objects is improved by using novel Singular value decomposition (SVD). SVD compresses the size of saturation matrices using less memory. Singular value decomposition has better accuracy with 87% and F score of 83% compared with the Gaussian mixture model (GMM).

SVD removes the smallest singular values from the saturation matrices and gives more image quality than the existing algorithm (Coak et al. 2020). Local SVD Binary Patterns detect the potential structure that results in improved robustness in comparison with the existing algorithm (Guo, Xu, and Qiang 2016). SVD has higher efficiency and color information than GMM (Jlassi, Douik, and Messaoud 2010). Better intensity and texture variations of the image sequence results in a proposed algorithm compared with the existing algorithm. SVD performs video reconstruction with better quality and good sequence than GMM (Haldrup 2014). By low rank and sparse decomposition a video is performed to give effective output in SVD than the existing algorithm (Bouwmans, Aybat, and Zahzah 2016). SVD uses fourier transforms to give a clear output compared with the existing algorithm (Z. Wang, Fu, and Huang 2019). SVD is used to reconstruct three-dimensional objects from a two-dimensional video or image sequence (Hallinan et al. 1999). A watermark embedding technique is used in SVD to increase robustness (Richardson 2011).

In SVD by removing the singular values results in storage size reduction but cannot adjust internal sensitivity because of its low pixels. The Hybrid color space is not efficient for all the applications in SVD. The SVD algorithm deals with the intrinsic rank of the matrix, rather than the size of the actual video (data) matrix. While constructing three dimensional images from two-dimensional video streams, the objects can be missed and undetected in SVD. The project's goal is to detect real-time objects in images or videos in real time. Around the detected objects, bounding boxes are drawn. Future improvements can be concentrated by putting the project on a system with a GPU for faster results and more accuracy.

CONCLUSION

In this work, a Singular Value Decomposition algorithm (SVD) is proposed for foreground detection in dynamic scenes. Here SVD is compared with the Gaussian Mixture Model (GMM) by measuring F-score and accuracy. The mean F-score rate obtained for sample 10 images is 83% for Singular value decomposition algorithm and 79% for GMM. This shows that the proposed algorithm has a better mean F-score compared to the existing algorithm. The mean accuracy rate obtained for sample 10 images is 87% for Singular value decomposition algorithm and 85% for GMM. This shows that the proposed algorithm has a better mean accuracy compared to the existing algorithm.

DECLARATION

Conflict of Interest
No conflict of interest in this manuscript.

Author Contribution
Author GS was involved in writing the code for the Singular Value Decomposition for the foreground detection and manuscript writing. Author PJ was involved in Guiding to analyze the performance, data validation, and the review of the manuscript.

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TABLES AND FIGURES

Table 1. F-score obtained for sample 10 images where the mean Fscore rate is 83% for Singular value decomposition (SVD) algorithm and 79% for Gaussian Mixture model (GMM).

Singular value decomposition (SVD- Group 1)	**Gaussian Mixture Model (GMM- Group 2)**
0.8140	0.7890
0.8160	0.7928
0.8165	0.7980
0.8180	0.7980
0.8200	0.7982
0.8220	0.7900
0.8230	0.7990
0.8290	0.8000

0.8350	0.8170
0.8420	0.8220

Table 2. Accuracy obtained for sample 10 images where the mean accuracy rate is 87% for Singular value decomposition (SVD) and 85% for Gaussian Mixture model (GMM).

Singular value decomposition (SVD- Group 1)	**Gaussian Mixture Model (GMM- Group 2)**
0.8700	0.8452
0.8726	0.8453
0.8741	0.8454
0.8750	0.8454
0.8752	0.8500
0.8756	0.8510
0.8757	0.8518
0.8758	0.8520
0.8800	0.8530
0.8820	0.8540

Table 3. Represents descriptive statistics for both sample groups.

	N	**Minimum**	**Maximum**	**Mean**	**Std.Deviation**
Fscore	20	0.7890	0.8420	0.812475	0.0150382
Accuracy	20	0.8452	0.8420	0.862455	0.0139081

Table 4. Represents group statistics for both sample groups.

	Groups	**N**	**Mean**	**Std.Deviation**	**Std.Error Mean**
F Score	SVD	10	0.823550	0.0090996	0.0028775
	GMM	10	0.801400	0.0110478	0.0034936
Accuracy	SVD	10	0.875600	0.0033912	0.0010724
	GMM	10	0.849310	0.0035890	0.0011349

Table 5. Represents the statistical analysis of independent sample tests for both sample groups.

						Significance		**T-test for equality of means**		**95% confidence interval of the difference**	
		F	**Sig.**	**t**	**df**	**One -sided p**	**Two sided p**	**Mean Difference**	**Std.Error Difference**	**Lower**	**Upper**
Fscore	Equal variances assumed	.327	.575	4.894	18	<.001	<.001	.0221500	.0045261	.0126410	.0316590
	Equal variances not assumed			4.894	17.363	<.001	<.001	.0221500	.0045261	.0126159	.0316841
Accuracy	Equal variances assumed	1.231	.282	16.837	18	<.001	<.001	.0262900	.0015614	.0230095	.0295705
	Equal variances not assumed			16.837	17.942	<.001	<.001	.0262900	.0015614	.0230088	.0295712

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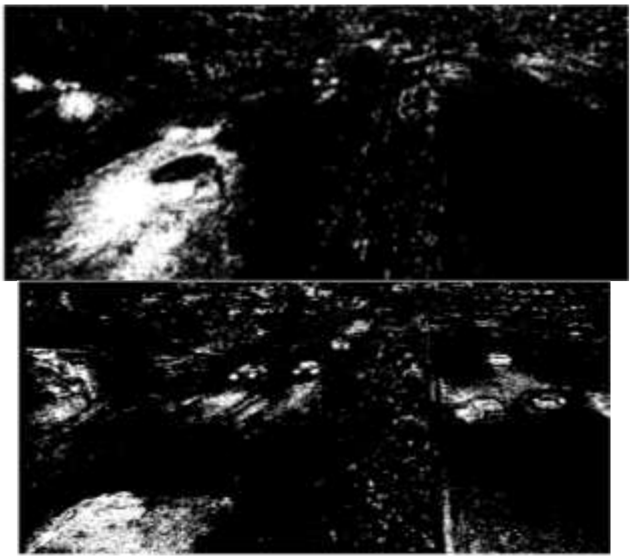
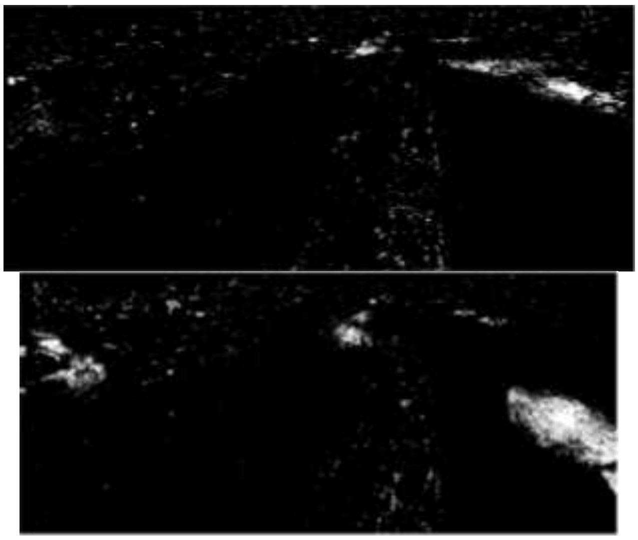
Fig. 1. Represents a set of input images of CdNet2014 dataset.





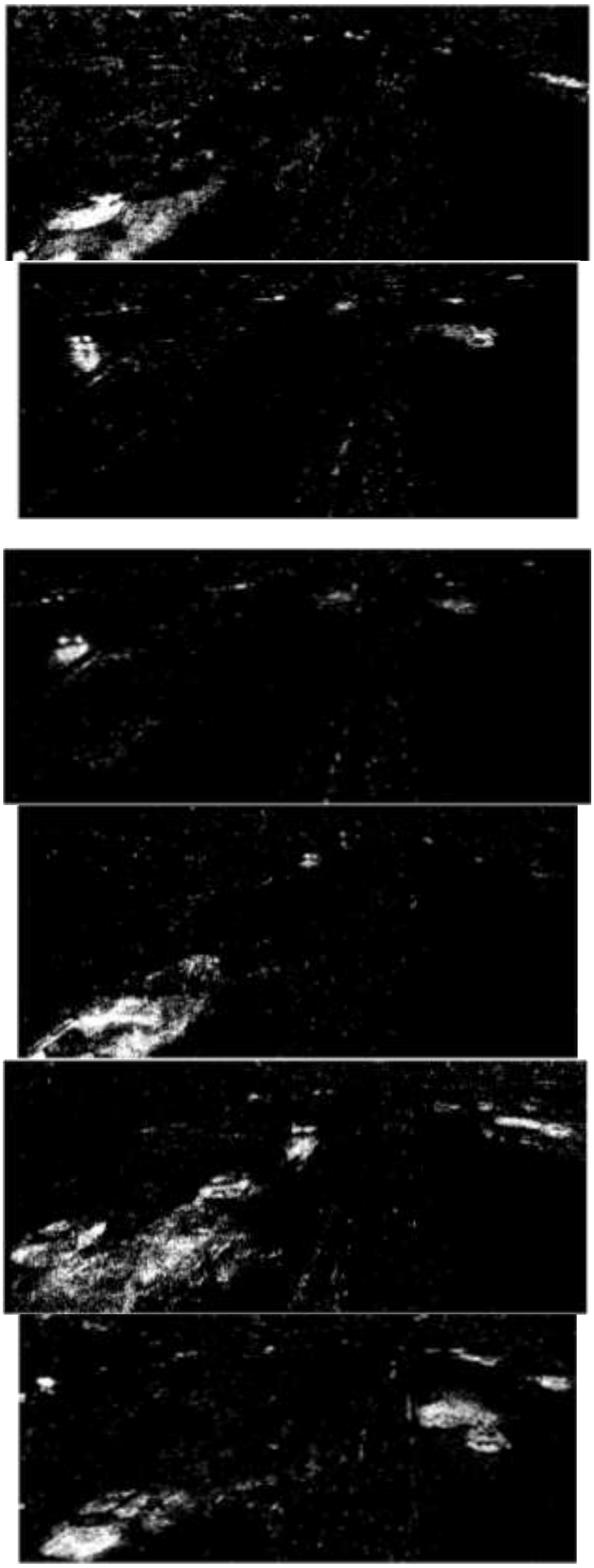
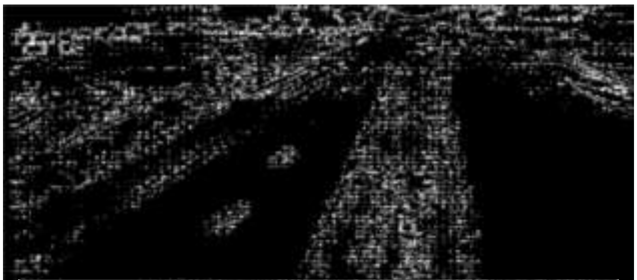
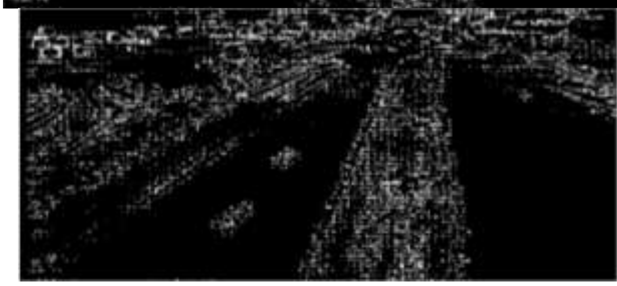


Fig. 2. The following figures represent a set of output images of SVD.





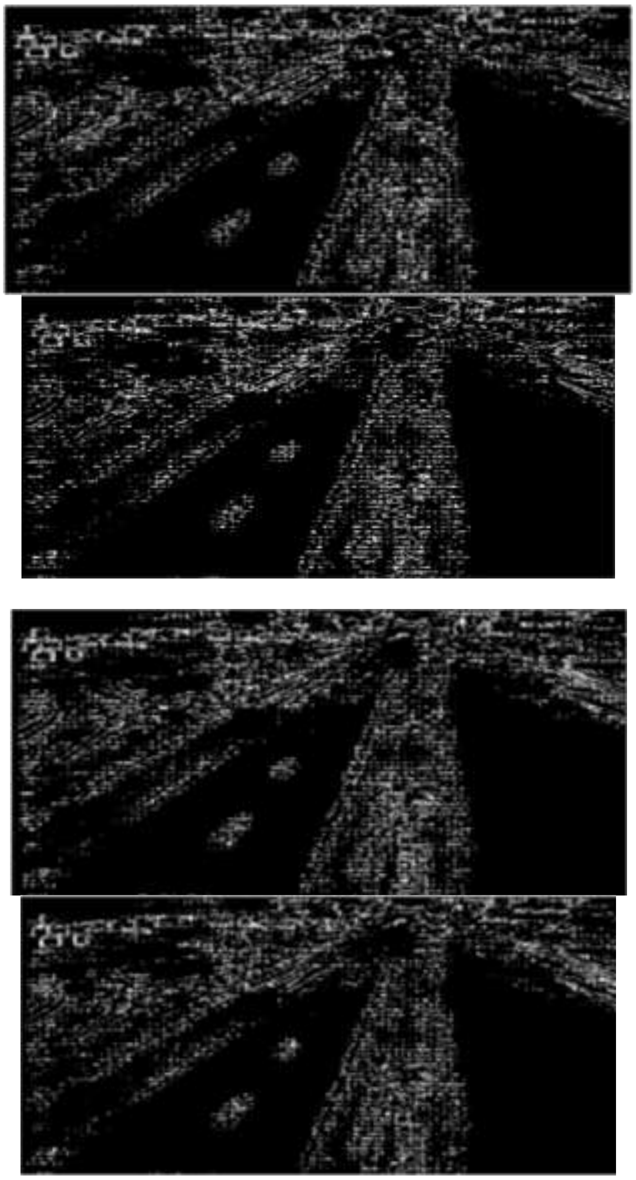


Fig. 3. Represents the set of output images of GMM.

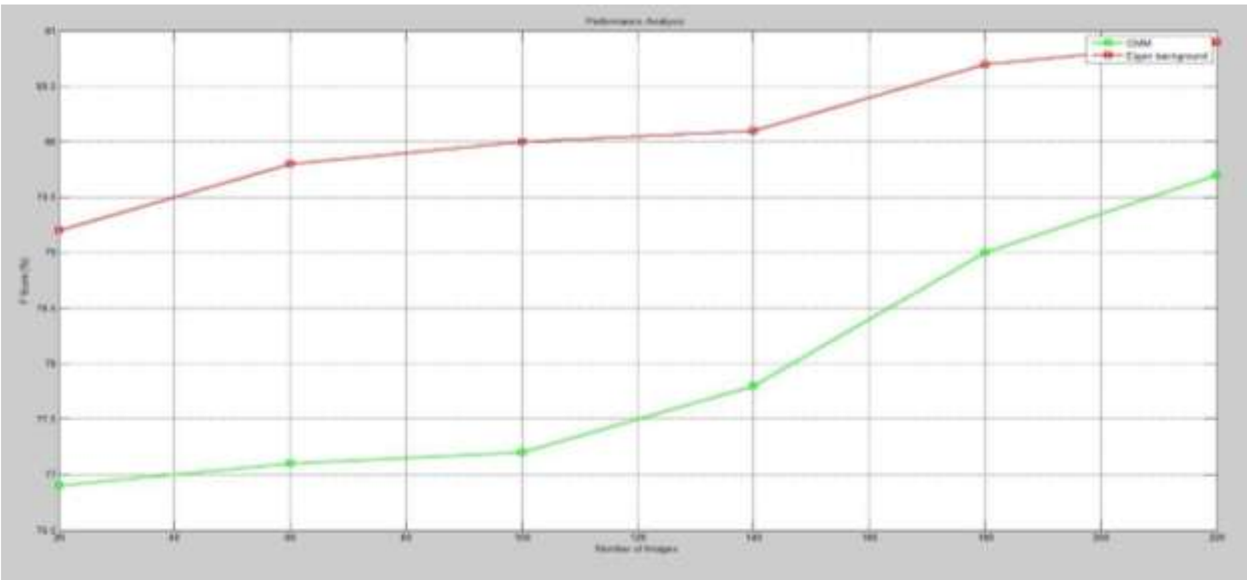


Fig. 4. The following figure shows the F-score graph between Singular value decomposition (SVD) and Gaussian Mixture Model (GMM).

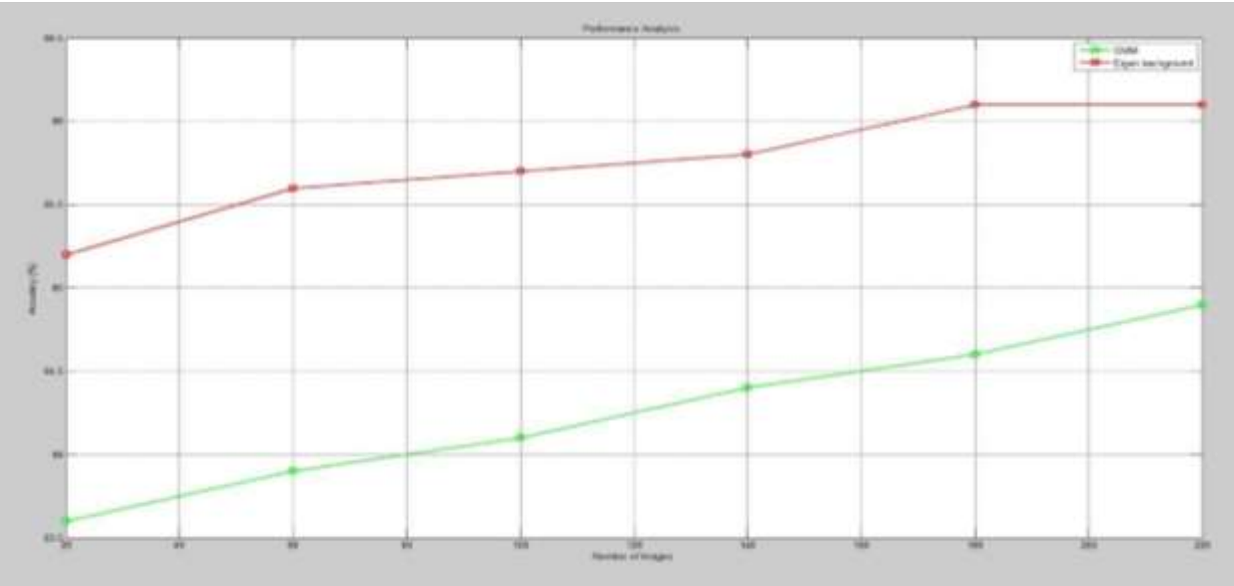


Fig. 5. The following figure shows the accuracy graph between Singular Value Decomposition (SVD) and Gaussian Mixture Model (GMM).

Fig. 6. Comparison graph for SVD (81.9%) and GMM (80%). This shows that the proposed algorithm has a better mean F-score compared to the existing algorithm.

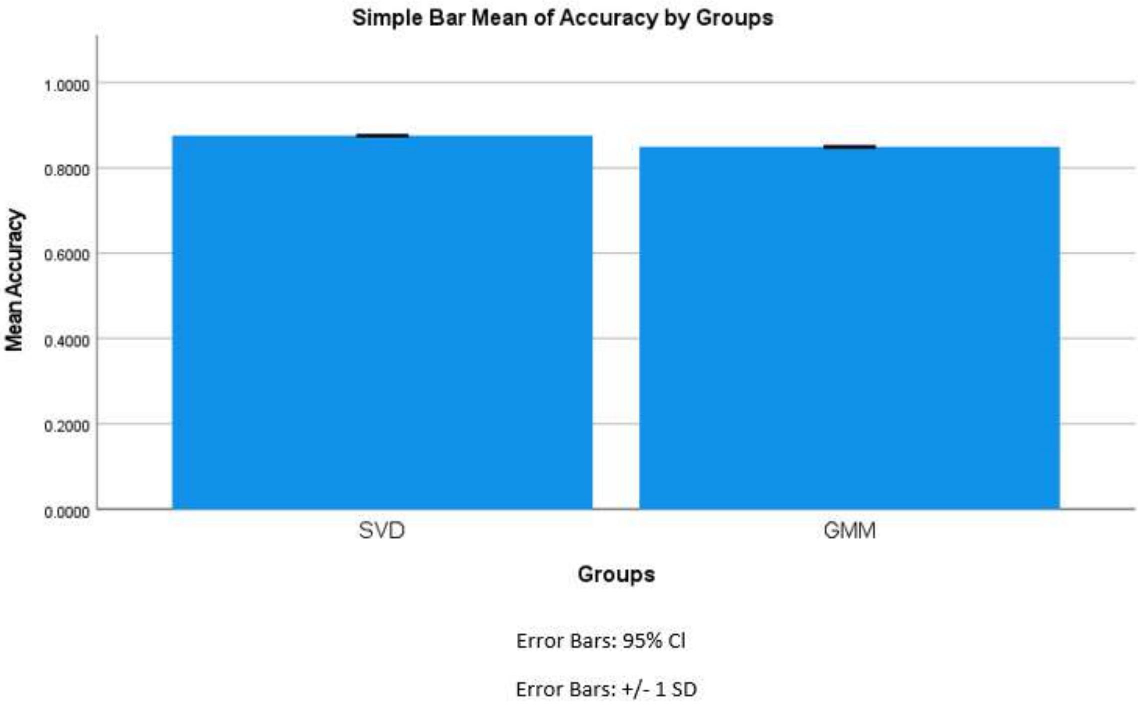


Fig. 7. Comparison graph for SVD (83%) and GMM (82%). This shows that the proposed algorithm has a better mean accuracy compared to the existing algorithm.