Efficient Feature Extraction from Multispectral Images for Face Recognition Applications: A Deep Learning Approach

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Abstract: In recent years many face recognition algorithms were used for the identification and authentication of a person to a system. However, still, feature extraction from multispectral images was considered to be a challenging task. Feature extraction, including highlight location and portrayal, assumes a significant job in real-time security-based applications. In this paper, a novel Geometric Algebra-based Multivariate Regression Feature Extraction (GA-MVRFE) algorithm was proposed to extract features from a huge dataset stored in the cloud efficiently. This proposed algorithm works with the supreme expedient deep learning approach - Convolutional Neural Network (CNN) for image classification. CNN will automatically detect significant features from the multispectral images without any human intrusion from a huge database. Real-time images were captured with three different cameras and applied filters over the images and were created as a dataset. To show the competence of the proposed algorithm, an exclusively created dataset with a set of 14,400 image data was applied in the proposed and other existing algorithms, and their efficiency and robustness were noted. Providentially, GA-MVRFE produced better accuracy in 'Face Recognition' with a less time fraction compared with former algorithms. Obtained accuracy % for Geometric Algebra Oriented fast and Rotated Brief (GA-ORB), Geometric Algebra Fast Retina key-point Extraction Algorithm (GA-FREAK), Trilateral Smooth Filtering (TRSF), Cross Regression Multiple View Features extraction (CRMVF) and GA-MVRFE was 87.81, 83.23, 90.72, 91.67 and 97.57 respectively.

1. Introduction
Digital Image Processing (DIP) handles and manages the control of captured pictures through any computerized handheld devices. Handling images and videos and extracting information from them for various applications requires a good skillset. Image processing includes capturing, pre-processing, and storing images. Classification and accessing of Multispectral images have been a tough task being carryout with various algorithms in recent years[1]–[4]. Where the preparation and testing stages generally have a similar training set, and the names of the preparing training set are already known and being used widely.

However, in a real-time image classification framework images will be given as input in a stream of flow. The framework can get new images coming in the stream to refresh the framework, which may contain novel classes that do not exist in the previous training set. It is essential to proficiently gain from these pictures without utilizing human comment exertion, particularly now we face the difficulties that real-time stream of image datasets were growing bigger and bigger. Time is taken for
capturing, processing, and comparison between images were considered to be the most important factor in a real-time environment [5], [6].

"Machine learning approach" was considered to be the only possible way to have a large set of image classification, which helps in the classification of real-time multispectral images[7]–[9]. Convolutional Neural Networks (CNN) have been recognized as best in class in a very limited ability to focus time concerning their high and outperforming execution as far as both precision and reliability[4], [8], [10], [11]. Deep learning profound various leveled portrayals requires an outstandingly bigger arrangement of the dataset of images than for conventional learning methodologies.

There are various applications of multispectral images being carried out irrespective of the fields. One of the widely used applications is the image-based Authentication System (AS)[12]–[15]. Image uprightness validation has stirred much concern these days because advanced images can be effectively modified, and the alteration is hard to be identified. As of now, an ever-increasing number of strategies are investigated to manage the issues of image adjustment. Image-based authentication and verification systems [21]–[26], [13]–[20] gets developing mindfulness because advanced images can be handily altered and the variations in RGB (Red, Green, and Blue) adjustment make the image difficult to recognize. Biometric authentication systems use Iris images and fingerprint images for authentication [23].

In this study, an efficient Geometric algebra Multivariate regression feature extraction (GA-MVRF) algorithm was developed for feature extraction from multispectral images. Complete image datasets were created with real-time images, applied filters over the images, and stored in a multi-dimensional array multivariate in the cloud data storage. To show the performances and metrics of this GA-MVRF algorithm, a dataset was applied to the other algorithms [27]–[31] which are capable of performing similar feature extraction techniques. Finally, the accuracy of each algorithm concerning feature extraction has been discussed in the results and discussion section.

2. Experimentation
In this paper, a novel GA-MVRF algorithm was proposed to determine the feature extraction from multispectral images in face recognition. To show the efficiency of the proposed, five different existing algorithms were compared, and their results were analyzed. Face images of 800 students were collected along with their personal information for identification with different shades of blue background color with different lighting conditions for the dataset. Further, the images were pre-processed classified with Convolutional Neural Network (CNN)-Deep learning approach of Machine Learning (ML). Colour filters were applied on the images for classifications like original, Grayscale, R, G, B, Black, and white to add various dimensions to the training set.

This study involves six stages, as shown in Figure 1. (i) Image Collection/Capturing, (ii) Preprocessing, (iii) Filter application, (iv) Feature extraction, (v) Classification, and (vi) Algorithm application and optimization.
Figure 1. Workflow diagram of this study.

Classified images were applied in the GA-ORB, GA-Freak, GA-MVRFE, TRSF, and CRMVF algorithms, and the optimizer block predicts the best accuracy of algorithms for the dataset applied.

2.1 Image Capture
Data set has been created with the portrait images captured from 800 students with different shades of a blue background and equal lighting conditions. Three different cameras viz 16MP HD Webcam with Microphone, Samsung On5 pro Backend camera and Canon EOS 1500D DSLR Camera were used for capturing images to get different pixel resolutions. Captured images from each camera were saved together in the form of multiset and assigned with a multi-labeled attribute for every single person's image. There were 800 images collected from each camera, put to gather, 2400 image set was created considering three images from each student.

2.2 Multi-filter application
An image set was created from the cameras, and classified, saved in the database along with a convolutional multispectral set. An exclusive front end was developed with Python programming to apply various filters over the images. Six different filters such as Grayscale, Red, Green, Blue, blur, and Black & white were applied to the original image and saved under the same dataset.
These six images were used as a data set in this study to analyze the efficiency of the algorithm developed. Figure 2 shows the sample dataset created with the implementation of filters. 2400 image dataset was applied with six filters, and a total of 14,400 datasets were formed.

2.3 Classification
Profound CNN is the most perfect and most developed visual examination technique for image processing. CNN's comprise of four sorts of layers—convolutional, enactment, pooling, and completely associated—each of which has an alternate job in finishing the ideal strategy.

![Image of Convolutional Neural Network (CNN) model]

Figure 3. Convolutional Neural Network (CNN) model
The image dataset was classified with the implementation of the Convolutional Neural Network (CNN) model, as shown in Figure 3. The convolutional layer makes include maps as per the heaviness of the neuronal contributions, where the mutual loads establish alter for each guide. Through these component maps, the efficacy of the convolutional layer increments, and overfitting is forestalled. The actuation layer follows the convolutional layer. The non-direct property of the actuation layer is required for the extraction of increasingly complex highlights from the info signals produced by the convolutional layer. Next is the pooling layer, which factually investigates the sources of info using moving square shapes and subsequently diminishes the affectability of the picture data to the movements. These layers resulted in a feature set and which was saved in the cloud repository.

3. Methodology
This section describes the significances of GA-MVRFE developed by comparing it with the other algorithms. This study was carried out with 85 % of the training dataset and 15 % of the test dataset of the total 14400 classified image dataset.

3.1 Implementation of Algorithms
3.1.1 Geometric Algebra Oriented fast and Rotated Brief (GA-ORB)

The GA-ORB algorithm [31] have extracted feature from multispectral images with high opinion to uniqueness and sturdiness in the extraction and identical concern points. Dataset of images used in this present study was applied in this GA-ORB algorithm, and the results of this GA-ORB was reported in Table 1 and Table 2. This shows that this GA-ORB took more inspection and interval time.

\[ T(A, B) = \sum_{x=1}^{m} C_x (A, B)y^t \]  \hspace{1cm} (1)

The above equation (1) shows T (A, B) a multispectral image. Here 'x' denotes the band value of the multispectral image; 'n' denotes dimensions of the multispectral image and (A, B) donate 2-Dimensional Coordinate. The result of the equation was each frame description from multispectral images. This algorithm resulted in the orientation of the feature used.

3.1.2 Geometric Algebra-Fast retina keypoint extraction algorithm (GA-Freak)

This GA-Freak algorithm had a positive factor for finding concern points in multispectral images. Real-time feature extraction was one of the key positive factors about this GA-Freak algorithm. This GA-Freak algorithm was applied over the dataset developed. The result of this GA-Freak showed some lag in computation time over the large dataset. Also, feature detection and face recognition accuracy were comparatively less. GA-Freak reported less accuracy (shown in Table 1) made it not suitable for feature extraction from multispectral images.

\[ P = \sum_{0\leq x, y} 2^k A(T_x) \]  \hspace{1cm} (2)

In this equation (2), T, 'x' denotes a pair of receptive fields, 'y' denotes the size of the descriptor. GA-FREAK descriptor of concern points was generated with orientation in GA-Space. The classification of the distance point's detection had produced less efficiency when the dataset applied in this algorithm.

3.1.3 Trilateral smooth filtering (TRSF)

TRSF is an algorithm to find the combination of two-pixel points says as a noise point in the process of filters from hyperspectral images. TRSF was applied over the dataset to prove the effectiveness of feature extraction by classification using SV machines. In our data sets from Table1 and Table2 combination of the two-pixel concept has difficult to show in feature detection and in computing time.
Neighborhood pixel distance can be calculated by $M_x$ shown in equation (3), $T_y$ was grayscale images to be used as an input and pixel position identified from neighborhood pixel set. Equation (3) was used to calculate the distance of pixel set in images for feature extraction. Time calculation very high to calculate computation time.

3.1.4 Cross Regression Multiple view Features Extraction (CRMFE)

The proposed concept of CRMFE has to find multi-viewpoint for feature extraction in images with low-dimensional matrix value. The regression-based concepts is a good technology to extract features from images. This concept is applied in our data sets for finding extraction and computation time using the multi-viewpoint method, but output accuracy is very less in image extraction.

$$T = \sum_{k=1}^{n} M_k N_k$$

Using this equation, we can calculate the low-dimensional projection for feature extraction from multispectral images. $M_k$ and $N_k$ used in our concepts as multi-view and final projection for image classification, but computation time was very less.

3.1.5 Geometric Algebra Multi-Variate Regression Feature Extraction (GA-MVRF)

Geometric Algebra facilitates free structure to make the calculations productively, which has been applied generally in image processing. As a rule, the geometric item is significant to the geometric variable based math hypothesis. Linear regression endeavors to demonstrate the connection between image correlation feature factors by fitting a direct condition to the multi-feature information with the implementation of two variables. One variable is viewed as an illustrative variable, and the other is viewed as a reliant variable.

Feature extraction was carried out as a procedure of dimensionality decrease by which an underlying arrangement of the unprocessed dataset was diminished to increasingly sensible gatherings for handling. An attribute of these enormous datasets required countless factors that required a great deal of figuring assets to process.

The proposed GA-MVRF algorithm can be summarized in the following steps:

Step 1: Apply multispectral image dataset to genomic algebra
Step 2: Build the multi-attribute labeled structure with filters applied in the equation (5)

$$I_{nl}(x, y) = \sum_{j=3}^{m} \sum_{i=1}^{G} R_{Li}, B_{Li}, W_{Li}$$

Step 3: Apply multivariate regression function $M_r = u + vS$, where $S$ is the illustrative variable and $M_r$ is the dependent variable
Step 4: Compute the time and placement of the image feature set.

Exclusively developed GA-MVRF algorithm was compared with GA-ORB, GA-FREAK, TRSF, and CRMF in feature extraction from multispectral image for finding feature of algorithm and computation time. However, GA-ORB and GA-FREAK dealt only with uniqueness without robustness in multispectral images; as a result, computation time was very high. Then the dataset was applied in TRSF and CRMFE with multispectral images and got the only closest point of view of image extraction. Feature identification in both algorithms was found to be less to compare with GA-MVRF. Four algorithms were compared with the data set and their efficiency, and computation time details were recorded. GA-MVRF algorithm was applied in the large image data set to find features and computation time. This algorithm produced both uniqueness and multi-viewpoint for feature extraction from multispectral original, Grayscale, RGB Color, Blur, and Black and White images.
4. Results and Discussion

Table 1 displays the result of algorithms on the features of the training set from multispectral images. The GA-MVRFE performed a various number of observations on Original, Grayscale, R, G, B, Blur, and Black & white images. A single thread running on an Intel i7-330N 3.76 GHz processor was used to execute the dataset, classify and evaluate the speed of various algorithms concerning feature points detection and feature extraction. Results of Table 1 shows GA-MVRFE was fastest on Original image, Grayscale, Red, Green, Blue, Blur, and Black & white image compare with GA-ORB, GA-FREAK, TRSF, and CRMFE.

Table 1. Application of algorithms on the features of the training set

| Algorithms       | GA-ORB | GA-FREAK | TRSF  | CRMUFE | GA-MVRFE |
|------------------|--------|----------|-------|--------|----------|
| Original         | Inspection | 1550     | 1205  | 950    | 655      | 550      |
|                  | Inliers(in %) | 60.5     | 85.62 | 96.77  | 88.91    | 75.65    |
| Gray Scale       | Inspection | 2560     | 1887  | 990    | 786      | 450      |
|                  | Inliers(in %) | 88.71    | 79.01 | 65.18  | 46.56    | 36.86    |
| Red Images       | Inspection | 1885     | 1563  | 1190   | 890      | 650      |
|                  | Inliers(in %) | 91.12    | 85.78 | 73.16  | 66.71    | 56.96    |
| Green Images     | Inspection | 1910     | 1645  | 1278   | 965      | 791      |
|                  | Inliers(in %) | 88.45    | 80.91 | 74.1   | 63.88    | 54.14    |
| Blue Images      | Inspection | 2016     | 1813  | 1432   | 1103     | 880      |
|                  | Inliers(in %) | 94.93    | 92.72 | 81.39  | 76.19    | 69.1     |
| Blur Images      | Inspection | 1356     | 1026  | 845    | 674      | 346      |
|                  | Inliers(in %) | 94.13    | 87.01 | 74.34  | 65.13    | 51.23    |
| Black and White Images | Inspection | 2438     | 1765  | 865    | 664      | 367      |
|                  | Inliers(in %) | 86.17    | 78.19 | 67.81  | 59.38    | 46.1     |
Table 2 shows correlated time for image feature extraction between different algorithms. Proposed GA-MVRFE and different algorithm efficiencies were calculated by two terms Inliers and Interval per inspection. GA-ORB had good computation time compared to other GA-MVRFE, GA-FREAK, TRSF, and CRMFE an Original image. The GA-MVRFE was the best efficiency in Grayscale, Red, Green, Blue, Blur, and Black & White among all other algorithms. The computation time of image extraction on GA-MVRFE had the fastest of all the other algorithms chosen.

Figure 4. Inspection values of algorithms with an $R^2$ value of 0.975

$R^2$ was calculated in Figure 4 to show a factual proportion of how close the information is to the fitted to the regression line. It is otherwise called the coefficient of assurance, or the coefficient of numerous assurance for various relapses. $R^2$ value above 0.97 indicates that the algorithm elucidates all the inconsistency of the response information and fits well with the data. Fig 4 also shows the inspection values of the GA-MVRFE algorithm with an $R^2$ of 0.975 for the original image feature. Results reported as 550, 450, 650, 791, 880, 346, and 367 for Original, Grayscale, R, G, B, Blur, and Black and White filtered images respectively.

Figure 5. In linear values of algorithms
Figure 5 shows the Inlinear values obtained for this GA-MVRFE and other algorithms compared. It clearly shows that the lesser the non-linear values greater the efficiency. Original image recorded a higher and non-linear value for the proposed algorithm compared to GA-ORB, but the time taken for computation is very less with each other.

**Table 2.** Comparison of computation time taken by each algorithm for the feature set.

| Algorithms      | GA-ORB | GA-FREAK | TRSF | CRMVF | GA-MVRFE |
|-----------------|--------|----------|------|-------|----------|
| **Interval in (s)** | 75.34  | 96.13    | 100.22 | 99.82 | 84.16    |
| **Interval per Inspection in (ms)** | 60.5   | 85.62    | 96.77 | 88.91 | 75.65    |
| **Interval in (s)** | 98.14  | 87.77    | 71.78 | 54.23 | 50.32    |
| **Interval per Inspection in (ms)** | 88.71  | 79.01    | 65.18 | 46.56 | 36.86    |
| **Interval in (s)** | 120.1  | 97.89    | 85.67 | 74.23 | 68.29    |
| **Interval per Inspection in (ms)** | 91.12  | 85.78    | 73.16 | 66.71 | 56.96    |
| **Interval in (s)** | 119.18 | 98.45    | 86.89 | 76.23 | 59.01    |
| **Interval per Inspection in (ms)** | 88.45  | 80.91    | 74.1  | 63.88 | 54.14    |
| **Interval in (s)** | 122.31 | 101.34   | 90.23 | 81.45 | 62.19    |
| **Interval per Inspection in (ms)** | 94.93  | 92.72    | 81.39 | 76.19 | 69.1     |
| **Interval in (s)** | 96.45  | 90.1     | 78.9  | 69.37 | 56.34    |
| **Interval per Inspection in (ms)** | 94.13  | 87.01    | 74.34 | 65.13 | 51.23    |
Figure 6. Interval Vs Interval per inspection of algorithms

Figure 6 shows the result of Interval versus Interval per inspection. The proposed GA-MVRFE has taken less interval compare with the other models. The other algorithms in Figure 6 interval value were recorded with the next lesser value to GA-FREAK, and other algorithms were noted with a very high interval rate.

Table 3 portrays the efficiency comparison between the algorithms based on profit points and time taken for processing. The final result of our proposed algorithm GA-MVRFE was the best efficiency in Feature extraction on computation time and profit points from multispectral images.

Table 3. Efficiency comparison between the algorithms based on profit points and time is taken for processing
FREAK
TRSF  890  18.78  935  20.12  1045  22.90  1109  25.65
CRMVF  979  22.16  1089  24.35  1130  25.10  1190  28.67
GA-MVRFE  1020  2.16  1103  2.89  1045  3.12  1300  9.13

Figure 7. Stock chart for intervals in seconds for the algorithms chosen

The stock charts display the fluctuations among the data recorded for various algorithms used in this study. Details of the time consumption are given in Figure 7. As a highlight, this Figure Seven clearly shows that GA-MVRFE had taken 12 seconds to extract features from multispectral images.

Figure 8. Output of the GA-MVRFE algorithm

The final output of the proposed algorithm, as shown in Figure 8. During real-time implementation, this algorithm provides a face feature comparison accuracy in a label along with the name, gender, and
age. Further, to denote males, the identifier box will be displayed in blue color; For females, the identifier block will be displayed in pink color.

![Figure 9. Correlation between % Accuracy and Computation time](image)

Correlation between % accuracy and computation time was shown in Figure 9. From Fig, it is evident that GA-MVRFE produced higher % accuracy with lesser computation time.

5. Conclusion
Faster feature retrieval from the large image dataset was always considered to be the most challenging task. This study leads a CNN, Regression, and GA based fastest feature selection algorithm GA-MVRFE. The accuracy of this proposed algorithm was tested with 85% of the training dataset and 15% of the test dataset. 97.57 % of accuracy was obtained for GA-MVRFE. Efficiency and robustness were verified with various iterations of real-time data. This proposed algorithm recognized the faces crossing the fixed web camera and captured those images and tagged them with the name, age, and gender, and recorded the people's presence. This algorithm also identified multispectral images and performed group tagging over the subjects pass by the camera. Though this algorithm performed well with a people group, the accuracy was better only for a group maximum of 7 persons. Over 7, the accuracy has been reduced. This could be sorted out in future works.

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