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Influence Analysis of Image Feature Selection TechniquesOver Deep Learning Model

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ABSTRACT

The digital images are the data storage methods which store the real world information on a matrix based on pixels. The images are now become very valuable due to increasing applications in medical, engineering, and social. Therefore, Image processing and Classification plays an essential role. In this paper, we are investigating the employment of three different features i.e., shape, color and texture for image classification. In addition, the combined feature is also used for demonstrating the impact on classifier. The Deep learning based Convolutional Neural Network is used for feature and their combination classification. In this experiment, Diabetic Retinopathy Detection dataset is used.The performance of the model is evaluated in terms of accuracy which demonstrates the feature selection techniques are able to improve the classification accuracy and also minimize the resource utilization.

***Keywords:*Color Feature, Feature Selection, Image Classification,Shape Feature, Texture Feature.**

1. INTRODUCTION

Digital images are a technique of capturing and storing the real world data in form of sparse vector. The images are playing essential role in various real world applications such as in engineering, medical, media and advertisements and many more. Additionally, the growth in internet and communication technology i.e.5G increases the application of images. In this context, the analysis and investigation of image classification techniques is an essential domain of study. By using the images and machine learning (ML) a number of applications can be developed such as plant leaf imagebased disease detection, cancer cells analysis, manufacturing defect analysis and many more.

The machine learning techniques based image classification and analysis requires three key steps i.e. data preprocessing, feature extraction and classification. The preprocessing techniques are used for filtering and balancing the noise on image data. In addition, some normalization process may also involve. The second step is to obtain the image features using various kinds of feature selection techniques. The aim of feature extraction techniques may involve the identification of color distribution in image, and shape and objects hidden in image. Finally, we can use the features for classifying the objects based using machine learning algorithms.Additionally, the influence of feature selection technique on the machine learning algorithm's performance has also been measured. In addition, we have also proposed to investigate the combinations of the features and their impact on classification algorithms performance.

The feature selection techniques are useful in enhancing the valuable insights in image and minimize the amount of data to be process. The key insights have used for enhancing the accurate classification of the images, similarly the minimization of data can improve the efficiency in terms of time and memory utilization. Thus, we have needed to identify which kind of feature selection technique has more benefit for performing the classification with higher accuracy and low computational resource consumption. However, there are a number of feature extraction techniques available, some of them are classical and some of them are new. But each kind of feature has their potential and limitations. Additionally, each feature extraction techniques are process image data differently. Therefore, the image feature selection techniques may demonstrate different behavior with different applications and ML algorithm's performance.The main objective of this work involves the following:

1. Study of different image feature selection techniques
2. Study of performance influence with individual feature selection techniques
3. Study and measuring the performance influence using combination of feature selection techniques

2. LITERATURE SURVEY

This section offers the study of recent work which has been done in the area of image processing and their relevant applications.

2.1Feature selection based image classification

Y. Bi et al [1] propose a ensemble learning structure utilizing GP (EGP). The strategy incorporates feature learning, classifier choice, learning, and mixing into a solitary program. To accomplish this, a program structure, another function set, and a terminal set are created. The exhibition of EGP is inspected on nine image data collections. The outcomes exhibit EGP accomplishes better execution. The investigation uncovers that EGP advances great groups adjusting variety and exactness. ***Z. F. Lai et al [2]*** propose a deep learning model that coordinates Coding Network with Multilayer Perceptron (CNMP), which consolidates significant level features from a Convolutional neural organization (CNN) and classical features. The model incorporates (1), preparing CNN as a coding organization, and the result encodes pixels into feature vectors. (2) Extracted a bunch of conventional features (3) plan a model in light of neural organizations to meld the various features. The model accomplishes classification precision of 90.1% and 90.2%.

M. K. Alsmadi et al [3] show the extraction of hearty and significant features and storage. The feature contains color, shape, and texture highlights. A likeness assessment with a meta-heuristic calculation has been achieved between the QI elements and dataset pictures. The distance measurements are utilized to find the pictures. The CBIR methods are depicted and developed. These strategies increment the recovery execution. As indicated by ***Dr. A. Nazir [4]***, medical nutrition therapy (MNT) is a basic part of diabetes the board. A sound eating regimen is an eating routine that gives the supplements your body needs. Individuals with diabetes are urged to pick an assortment of fiber-containing food sources, like entire grains, organic products, and vegetables since they give nutrients, minerals, fiber, and different substances. The essential dietary fat objective in people with diabetes is to restrict immersed fat and cholesterol admission.

A picture recovery strategy is proposed by ***M. J. J. Ghrabat et al [5]***. This plans to recover pictures utilizing the best element extraction process. Gaussian sifting strategy is utilized to eliminate undesirable information. Highlight extraction is applied, like surface and shading. The surface is sorted as a dim level co-event network and shading as power-based elements. These highlights are grouped by k-implies. An adjusted hereditary calculation is utilized to improve the elements and characterized utilizing an SVM-based CNN. The presentation is assessed as far as responsiveness, particularity, accuracy, review, recovery, and acknowledgment rate. ***N. Varish et al [6]*** a various leveled picture recovery conspire to utilize shading, surface, and shape visual substance is proposed. This lessens the looking through space. The shape included has been registered by a basic combination of histograms and invariant minutes. The recovery kept pictures into the transitional dataset. Then, the surface has been processed. This gives the multi-goal pictures and the nearby calculation. The dim level co-event lattice-based surface is gotten. The vast majority of the unessential pictures are disposed of yet a few undesired pictures are left. Combined shading data is caught on both non-uniform quantized shading parts. At last, the shading highlight creates the ideal outcomes and low computational upward with better precision.

2.2. Applications of image classification

S. S. Yadav et al [7] explore how to apply the CNN on a chest X-beam dataset. The strategies are, SVM with neighborhood turn and direction free elements, move learning on two CNN models: VGG16 and InceptionV3, and container organization. The outcomes show that an increase is a viable way. Additionally, Transfer learning is helpful on a little dataset. In move picking up, retraining on an objective dataset is fundamental to further develop execution. ***Q. Liu et al [8]*** present a clever connection-driven semi-directed structure. It is a consistency-based technique that takes advantage of the unlabeled information to create excellent consistency. Present an example of connection consistency (SRC) by displaying the relationship among tests. The system authorizes the consistency of semantic connection among various examples, to investigate additional semantics. The analyses on datasets for example ISIC 2018 and ChestX-ray14 show predominance.

X. Yang et al [9] exploit profound learning methods to address hyperspectral picture characterization. This technique can take advantage of both spatial and ghostly relationships to upgrade grouping. They advocate four models, specifically 2D-CNN, 3D-CNN, repetitive 2D-CNN (R-2D-CNN), and R-3D-CNN. They directed trials in view of six informational collections. Results affirm the prevalence of the profound learning models. ***R. J. S. Raj et al [10]*** presented a superior classifier i.e., Optimal Deep Learning (DL) for order of cellular breakdown in the lungs, cerebrum picture, and Alzheimer's. The Classification is fusing preprocessing, including choice, and grouping. The objective is to infer an ideal component choice model to upgrade the exhibition utilizing the Opposition-based Crow Search calculation. The OCS picks the ideal highlights, here Multi-surface, dark level elements were chosen. The outcomes were contrasted and existing models and classifiers. The model accomplished the greatest presentation as far as exactness, awareness, and particularity being 95.22%, 86.45 %, and 100 percent.

2.3. Review summary

The recent literature about the image classification has been explored and found that the images are classically utilized with the information retrieval and medical image analysis. In this context, various methods for image classification and image retrieval techniques have been studied. During this study we have found there are various kinds of image feature extraction techniques are used which will help for data classification or retrieval of accurate information.

3. PROPOSED MODEL

This section involves two parts first contains the different algorithms used n this study. And the second section includes the proposed experimental model.

3.1. Algorithms used

A. Local Binary Pattern

In the picture, LBP [11] is calculated by equating it with its neighbors:

$$LBP_{P,R} = \sum_{P=0}^{P=1} s(g_p - g_e)2^P$$

$$s(x) = \begin{cases} 0 & x \geq 0 \\ 1 & x < 0 \end{cases}$$

Where, the center pixel is g_e , and neighbor pixel is given by g_p, P is number of neighbors and radius is given by R. if we considering a pixel coordinate (0, 0), then the g_p is calculated by

$$\left(Rcos\left(\frac{2\pi p}{P}\right), Psin\left(\frac{2\pi P}{P}\right)\right)$$

The neighbor values are not in grids can be projected by exclamation. Presume the image is of size I*J afterward the LBP design of every pixel is recognized, a histogram is constructed to signify the image:

$$H(k) = \sum_{i=1}^{I}\sum_{j=1}^{j} f\left(LBP_{p,r}(i,j), k\right), k \in [0, k]$$

$$f(x,y) = \begin{cases} 1 & x = y \\ 0 & otherwise \end{cases}$$

Where, K is the greatest LBP design value,U is described as the number of spatial growth (0/1 changes) in that design

$$U(LBP_{P,R}) = |s(g_{p-1} - g_e) - s(g_0 - g_e)| + \sum_{p=1}^{p-1} |s(g_p - g_e) - s(g_{p-1} - g_e)|$$

The unchanging LBP refer to the designs which have partial changeover ($U \leq 2$) in the spherical binary performance. The plotting from $LBP_{P,R}$ to $LBP_{P,R}^{u2}$ has P*(P-1) +3 yield values, with a search table of 2^P elements in irregular design could be described as:

$$LBP_{P,r}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} s(g_p - g_e) \; if U(LBP_{P,R}) \leq 2 \\ P + 1 \; otherwise \end{cases}$$

The conversion from $LBP_{P,R}$ to $LBP_{P,R}^{u2}$ have contain P+2 output values.

B. Grid Color Moment

This feature is widely utilized types of feature. These features demonstrate enhanced constancy and are more tactless of picture. Color is not only used for prettiness of image in also provides additional info. In color indexing, the goal is to recover all the pictures whose color configurations are analogous to image query. The feature vector is called "Grid-based Color Moment": [18]

- Transform image RGB to HSV
- Next convert the whole image into 3x3 blocks
- For each blocks
- Compute mean color

$$x' = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Where N is the number of pixels and x_i is the pixel strength.

- Calculate its variance

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - x')^2$$

- Compute its skewness

$$\gamma = \frac{\frac{1}{n}\sum_{i=1}^{N}(x_i - x')^3}{\left(\frac{1}{n}\sum_{i=1}^{N}(x_i - x')^2\right)^{3/2}}$$

- Individual block have total of 9 features, therefore the entire image has a total of 81 features. In order to use these features we need to normalize them. To do the standardization, for every features, Calculate the mean from the dataset

$$\mu = \frac{1}{M}\sum_{i=1}^{M} f_i$$

$$\sigma = \sqrt{\frac{1}{M}\sum_{i=0}^{M}(f_i - \mu)^2}$$

Where M is the number of pictures, and f_i is the article of i^th^ sample. The "whitening" alters for all the data, and get the regularized feature:

$$f'_i = \frac{f_i - \mu}{\sigma}$$

C. Sobel Operator

The Sobel operator carries out 2-D spatial gradient computation and considersareas of high spatial frequency relevant to edges. In an input image this operator fined the absolute gradient level. This operatorcomprisesa couple of 3×3 convolution kernels, which is demonstrated in Figure 1. The aim of these kernels is to identify edges vertically and horizontally. The kernels can be applied, to produce separate computation of the gradient components.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Figure 1: Sobel kernels

Both the kernels can be combined to find the absolute gradient magnitude using:

$$|G| = \sqrt{Gx^2 + Gy^2}$$

Typically, it is computed using:

$$|G| = |Gx| + |Gy|$$

The angle of orientation of the edge to the gradient is calculated by:

$$\theta = \arctan\left(\frac{Gy}{Gx}\right)$$

D. Convolutional Neural Networks (CNN)

The specialists have battled to create a framework that can comprehend visual information. This field is known as Computer Vision. PC vision fostered an AI model that outperformed the best picture acknowledgment calculations, known as AlexNet, with an 85% exactness. At the core of AlexNet was Convolutional Neural Networks an extraordinary kind of neural organization that generally mirrors human vision.

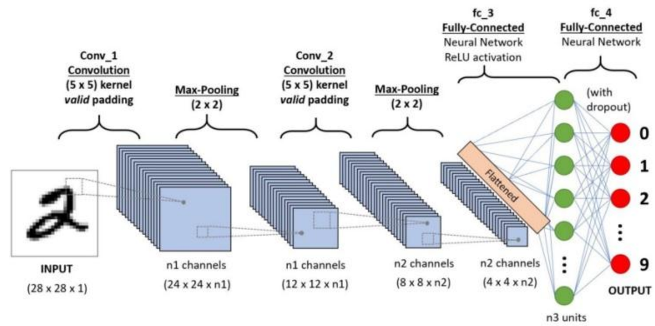

Figure 2: Basic CNN example model

CNN was for the most part used in the work of post offices where that is used for identification of areas and the pin codes and others. The major thing with the deep learning is that it requires a large amount of data to train and relevantly computational resources are required. That is a disadvantage of CNNs. The CNN is just a variant of deep learning architecture;these architectures are basically used for computation of visual objects. It utilizes an extraordinary strategy called Convolution. The aim of this convolution is to reduce down the image size which is easy and efficient for processing without loss of the essential features in the images which is required to recognize.

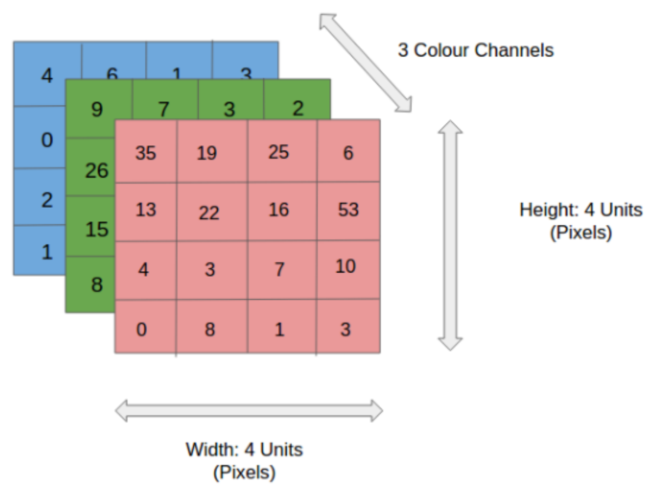

Figure 3: Image color channels

An RGB picture is a lattice of pixels having three planes. Figure 4 shows what a convolution is. We take a channel/bit (3×3 lattice) and apply it to the info picture to get a component. This convolved highlight is given to the following layer. CNN is made out of different layers. The layers are made with the neurons, which are the computational functions that are used for calculating the weighted sum of input and usages activation for producing the results of layer. The layers involved in network have generating the input for next layer of the network. The initial layers of the network are computing the features form the images such as edges or shape.

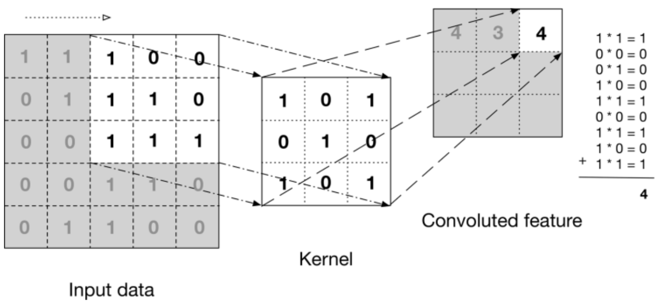

Figure 4: Kernel convolution process

As the output of one layer is passed to another layer the network will uncover the more complex features. In light of the actuation map, the final layer produces a score value which is most relevant to the final class label of object. There are two types of Pooling layer used i.e.,max and average pooling. The aim of these layers to improve the efficiency of data processing by minimizing the size of input samples.

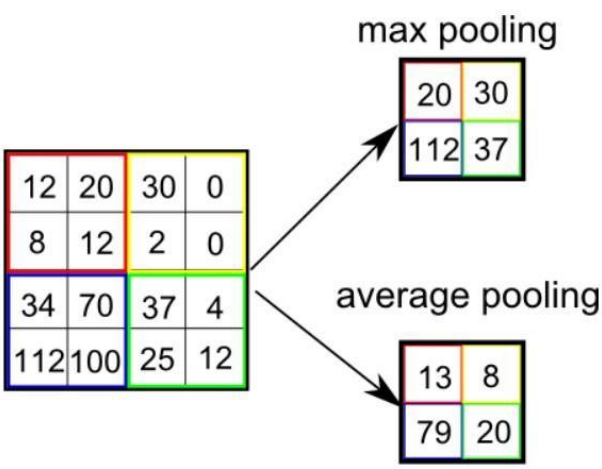

Figure 5: Pooling layer working

3.2Proposed System Architecture

The proposed system architecture for finding the impact of feature selection on deep learning algorithm is demonstrated in figure 6.

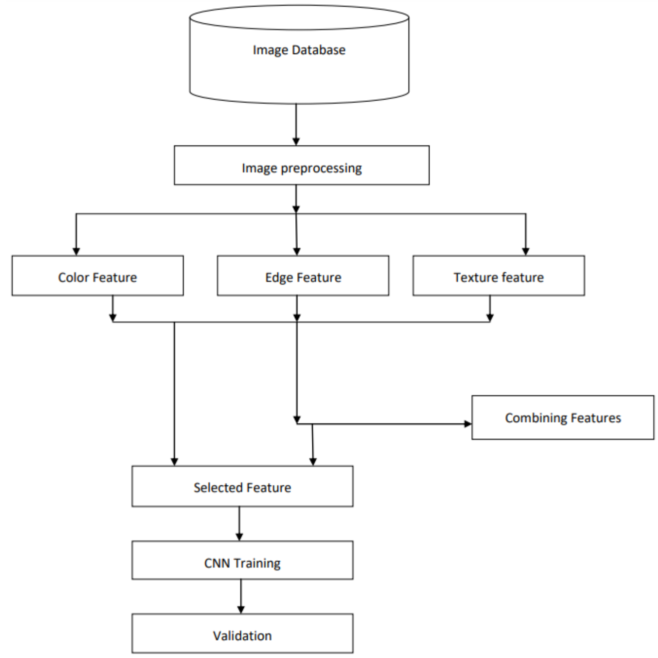

Figure 6: System architecture of proposed work

The first component of our model is image dataset. We obtained our dataset using the Kaggle repository. There are a number of image datasets are available among them we have selected the Diabetic Retinopathy Detection dataset [12]. The dataset has a set of retina images captured under different imaging circumstances. These set of images are marked with a subject id. A clinician has rated the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale:

- Class 0 shows Notpresent DR
- Class 1 shows Mild presence DR
- Class 2 shows DR Moderate
- Class 3 demonstrate Severe level of DR
- Class 4 shows Proliferative DR

The aim is to prepare a data model which is able to provide a score according to the above given classes. Therefore, the proposed work involves the recognition of images into five different classes. In order to utilize the image dataset, we have required to preprocess the images using the following formula:

$$I' = \frac{I}{255}$$

Next, we have employed feature selection technique to obtain features from the images. The feature selections techniques are very important process in image processing that are utilized for two major reasons:

1. Enhancing the useful insights from the input images data

2. Reducing the size of data for improving the efficiency of learning algorithm

There are three different features namely edge, color and texture has been extracted from the input images. In this context the following process is used to generate the set of features to be train with the learning algorithm.

Algorithm 1: Extracting image Features

Input: preprocessed images P

Output: image features Color C, texture T_{LBP}, Edge E_{SO}, Combined Features Com

Process:

1. $P_n = readImages(P)$
2. $for(i = 1; i < n; i++)$
    a. $C = P_i.GetColorChannel$
    b. $T_{LBP} = LBP.getTexture(P_i)$
    c. $E_{So} = Sobal.GetEdges(P_i)$
    d. $Com = C + T_{LBP} + E_{SO}$
3. $end\ for$
4. $Return\ [C, T_{LBP}, E_{SO}, Com]$

In this experiment we have implemented a 2D Convolutional neural network (2D-CNN). The implemented CNN consist of the following configuration.

1. **Input layer:** it is a 2D Convolutional layer and having the input size of 60*60*1 for individual feature training and 60*60*3 for combined feature training. The input layer is configured with the 'ReLu' activation function.

2. **Max Pooling Layer:** here 2D max pooling layer has been applied with the kernel size 2*2.

3. **2D Convolutional layer:** this layer is configured with the "ReLu" activation function and kernel size is taken as 3*3.

4. **Max Pooling Layer:** here 2D max pooling layer has been applied with the kernel size 2*2.

5. **Flatten layer:** this layer is used to convert 2D features extracted by the 2D-CNN into a flat vector.

6. **Dense Layer:** that is the back propagation layer used for learning with the flatten features. This layer is configured with the "ReLu" activation function and 64 neurons.

7. **Output Layer:** that is also a dense layer and used here for producing the output of the network which consist of 5 neurons as the number of output variables and configured with the "SoftMax" activation function.

The extracted features from the feature's extraction phase has used with the 2D CNN based configuration described. The extracted features are first split into two sets training set and second are validation set in the ratio of 80% and 20%. The model will trained and validated using the following process.

Algorithm 2: Model validation

Input: color feature C, texture feature T_{LBP}, edge feature E_{SO}, combined features Com

Output: classification performance

Process:

1. $F = selectFeature(C, T_{LBP}, E_{SO}, Com)$
2. $[train, test] = F.split(F, 80, 20)$
3. $Model = CNN.Train(train)$
4. $[accuracy] = Model.validate(test)$
5. Return $[accuracy]$

4. RESULTS ANALYSIS

This section describes the performance of the deep learning model with different feature selection techniques and their combination in terms of accuracy. The accuracy is the measurement of correctness of the model, which can be defined using the ratio of total correctly classified samples over total samples to classify. That can also be measured using:

$$accuracy = \frac{total\ correctly\ classified\ samples}{total\ samples\ to\ classify}$$

The performance of the different feature selection approaches and their combination with the deep learning during the training is demonstrated in figure 7. The X axis of diagram shows the number of epoch cycles and Y axis shows the model performance with the increasing number of epochs. According to the obtained results the combined features are rapidly moving towards the convergence as compared to the individual features. Additionally, combined features are demonstrating the higher performance during the training of the model.

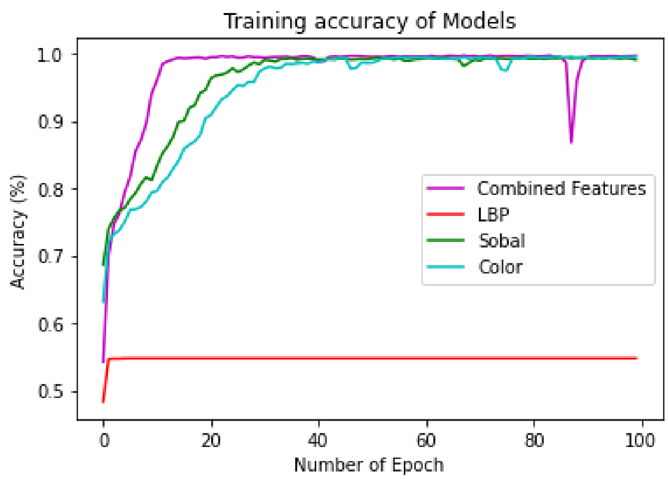

Figure 7: Training Accuracy of models

The training performance demonstrates the higher accurate results with the combined features, but when the models are validated against the test dataset, then we found the different behavior of model's outcome.

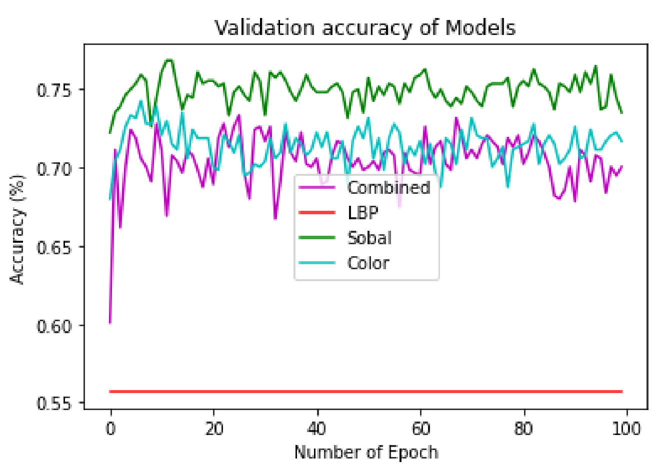

Figure 8: Validation accuracy of Models

According to the validation results the sobel operator and color feature demonstrate higher performance as compared to the combined features. The validation performance of the combined feature is highly fluctuating but fewer then the two other individual feature selection models.

5. CONCLUSION

The aim is to study the different feature section approaches for image data. The work also involves the measurement of performance influence of the classification algorithm due to feature selection approaches and their combination. In this context, an experiment has been designed based on the different feature learning models, combination and deep learning classifier. The experimental analysis has been carried out with a publicly available dataset which is used for diabetic retinopathy. The experimental analysis uncovers the following facts.

1. The feature selection techniques are useful for improving the classification accuracy as well as reduction in time and memory utilization.
2. Combination of features are not always advantageous but, in many applications,, it provides better consequences.
3. Not all the combinations of features are beneficial for all the application's use cases; we need variations and evaluation before utilization of the models before utilization.

This work will be extended in various new application use cases some essential of them are highlighted below:

1. Identify more methods for combining the features to improveclassification performance in global application utilization.
2. Prepare more variants of feature combinations which improves the accuracy.
3. Apply the feature extraction and combinations into more than one application for identifying the objects in image data.

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