Texture Extraction Methods Based Ensembling Framework for Improved Classification

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Abstract

Texture-based classification solutions have proven their significance in many domains, from industrial inspections to health-related applications. New methods have been developed based on texture feature learning and CNN-based architectures to address computer vision use cases for images with rich texture-based features. In recent years, architectures solving texture-based classification problems and demonstrating state-of-the-art results have emerged. Yet, one limitation of these approaches is that they cannot claim to be suitable for all types of image texture patterns. Each technique has an advantage for a specific texture type only. To address this shortcoming, we propose a framework that combines more than one texture-based techniques together, uniquely, with a CNN backbone to extract the most relevant texture features. This enables the model to be trained in a self-selective manner and produce improved results over current published benchmarks with almost same number of model parameters. Our proposed framework works well on most texture types simultaneously and allows flexibility for additional texture-based methods to be accommodated to achieve better results than existing architectures. In this work, firstly, we present an analysis on the relative importance of existing techniques when used alone and in combination with other TE methods on benchmark datasets. Secondly, we show that Global Average Pooling, which represents the spatial information, is of less significance in comparison to the TE method(s) applied in the network while training for texture-based classification tasks. Finally, we present state-of-the-art results for several texture-based benchmark datasets by combining three existing texture-based techniques using our proposed framework.

1. Introduction

Image texture analysis plays a vital role in multiple use cases. It has been used in medical imaging [16], remote sensing [30], industrial inspection of materials [26], autonomous vehicles [34], explosive hazard detection [23] and other industries. Image texture has numerous definitions which defines unique ways to calculate discrete qualities of texture like smoothness, roughness, uniformity, homogeneity, etc. These methods are based on the concept of repeating patterns in an image [17][27]. One use of texture analysis is that the Image’s texture classification enables better Image classification. The spatial distribution of pixels from an image is an integral part of texture classification [13]. Convolutional Neural Network (CNN) has been very successful in capturing the local and global spatial features, which play a key role in texture classification. CNN preserves the relative spatial information with the help of convolution layers and aggregates the spatial information using the pooling layers [29].

Local spatial features assist in recognizing the patterns of a texture. In an image, while classifying the texture, some local patterns are repeated throughout the image [27]. These local features exhibit almost the same characteristics as one another and they are extremely critical in differentiating the textures. The traditional CNN architectures do not exhibit phenomenal results for classifying the textures merely based on the spatial features.

The CNN can separate the local features with the aid of convolution layers although these spatial features are aggregated by employing the pooling layer. They make de-
cisions primarily based on the global features rather than focusing on the local features. CNN tends to lose the locally rich features and that’s the major reason behind the under-performance of CNN while identifying textures [6]. To overcome this problem, numerous techniques have been introduced where texture extraction (TE) layers are applied before the fully connected (FC) layers, using which local features are extracted. They are used along with global features. Several techniques such as DEPNet [29], DeepTEN [32], CLASSNet [6], FENet [28], etc., have been built based on this strategy.

Each of these methodologies focuses on some crucial aspects of texture and is specialized for specific use-cases. Using a Histogram layer [22] along with CNN produces adequate results, whereas FENet [28] produces the state-of-the-art (SOTA) results for some benchmark texture datasets. In this paper, inspired by DEPNet [29] where the the novelty is an ensemble of GAP and DeepTEN [32] techniques with bi-linear pooling delivering superior results, we propose a method where focused on combining several techniques rather than developing a new one. When various TE processes are combined, we can effortlessly capture the divergent characteristics of a texture in a better manner as each of these processes emphasizes unique aspects of texture. We achieved SOTA results on the major texture datasets by integrating distinct existing approaches i.e., DeepTEN, Histogram, and FAP [32] [22] [28]. These three techniques have been used with Global Average Pooling (GAP) in their original papers respectively. In our work, we have ensembled these techniques while removing GAP from each technique and tuning the size of their activation and hyper-parameter values to produce an optimized network with better generalization. By the implementation of this strategy, we achieve superiority over each method individually, since we enable classification of texture with distinct characteristics rather than an architecture focusing on any one major trait of texture.

2. Contribution

In this work we suggest a framework where more than one TE technique has been ensembled to achieve state-of-the-art (SOTA) results on bench-marked texture-based datasets.

In prior available research work generally two TE methods have been used in an ensembling architecture. However, we propose a framework that enables ensembling more than two techniques at the same time. For feature aggregation, prior research uses BLP but we apply concatenation in view of the fact that it reduces the number of parameters in the network. GAP has very less impact on the model when it is concatenated with another texture feature extraction technique. Whilst we are concatenating distinct techniques post convolution layer, we can replace the GAP with some other mechanism considering it makes a minimal impact on the model’s accuracy. Finally, using the proposed framework we have ensembled numerous feature extraction techniques demonstrating SOTA results on text-based bench-marked datasets.

Our proposed framework fixes a known design challenge. When an AI expert needs to solve a texture feature extraction problem or improve the results for a texture based dataset model, the first approach is typically to hand craft extraction of texture patterns, which is complex and requires domain expertise, involves experimentation to evaluate the diverse text extraction techniques. Our technique removes the need for hand crafting the extraction techniques by providing a holistic architectural solution which can extract a wide variety of textures in a diversified texture dataset.

We also demonstrate that unlike the other cited papers, GAP is not significant for texture specific images by using multiple experiments, which is a new theory on significance of GAP for texture-based images.

3. Main Idea

There is no single perfect method that works for all texture-based datasets. Combining multiple techniques specialized in learning different texture representations from images can enable improved learning. Inspired by the idea of passing related inputs along with the original input to yield better results, Pandey et al. [21], we employ the idea to pass additional informative features to enable better learning. By ensembling varied TE techniques, applied on top of the backbone architecture we build a model which is more efficient. This ensemble works by classifying texture based on a variety of texture features which are acquired using the individual TE techniques. Our experiments demonstrate that merging features extracted from dissimilar techniques improves the performance of model in comparison to an individual TE methods applied in isolation. Texture is the key feature for image classifications, and texture-based classification can assist in image classification tasks in many applications. Given the wide range of texture types embedded in different image datasets, we aim to construct a flexible and scalable model which can be used for a variety of texture-based datasets. From the previously developed techniques namely DeepTEN: Texture Encoding Network [32], DEPNet [29], DSRNet [30], etc. We can say that applying the texture feature extraction techniques after the activation layer of a backbone results in a better accuracy compared to techniques where the backbone is not used. Once the input image is passed through the backbone i.e., pre-trained weights of the convolution and pooling layers of the backbone model, subsequently local features, as well as the global features, can be examined to extract texture efficiently to classify the texture with improved precise-
ness. To produce an efficient ensemble model, we need to choose our methods astutely, as we don’t want to combine two techniques that are competent at doing the same task. We need to select the TE techniques in such a way that there is less correlation between the techniques to maximize the utilization of each technique while providing the best possible output. According to our idea, each technique which is chosen for the ensembled model should work on separate aspects of the data. This will ensure the smooth working of the model and will ensure that the resultant model is better than individual models. Using any specific technique for TE limits its use-case for a specific variety of textures. For other texture types that technique may not work. If one can use various methods in a single architecture then it would be able to handle complex texture types.

4. Related Work

Global Average Pooling (GAP) has been used for feature aggregation- TCNN [11] and wavelet CNN [11] are the most well known applications of GAP. This method is lossy regarding spatial information but is suitable for extracting the texture features [11]. The bi-linear pooling (BLP) introduced by Lin et al. [15] makes second-order interactions between the two outputs [9]- it is an outer product of each pair of feature points. BLP encodes more information than GAP. GAP also acts as a structural regularizer which enables us to explicitly enforce feature maps to classify the textures more efficiently [14]. DeepTEN [32] is a technique that uses residual dictionary learning to encode features on an end-to-end learning framework. It is different from SIFT [19] and filter banks [8] as hand-engineered features are used, but in DeepTEN method the dictionaries, features, classifiers, and encoding representation are all trained together to produce an orderless encoding. DeepTEN is very efficient for material and texture recognition tasks, and can also be used as a pooling layer on top of convolution layers to increase the flexibility of the model [16]. To integrate histograms with CNN, a histogram layer was introduced by Joshua [23], which captures the local spatial features using a histogram. The histogram layer uses a Radial basis function (RBF) [3] for the binning operation to find the bin centers and widths. It also uses make of the GAP to capture the spatial, texture, and orderless convolution features. The histogram layer enables the model to use fewer layers than conventional CNN, as the texture information is directly captured by feature maps [22]. Fractal analysis pooling (FAP) is used in FENet to group points of a texture based on the local fractal dimension of the image. It eliminates the dependency on spatial order while encoding the characteristics of features [28]. Fractal dimension is a quantitative measure of the roughness of a given image [24]. GAP is used to capture the spatial features of a texture but sometimes it fails to distinguish between complex distributive patterns from a texture. FENet uses both GAP and FAP as the method and distributive features are captured from distinct aspects [28]. Similarly, in this work, we propose a model architecture which exhibits an improvement in results by combining several techniques after the convolution layers. In the proposed model we consider the TE methods which extract properties from a single feature map unlike the class-net [6] where numerous feature maps are used to find the texture features.

5. Ensemble of TE Techniques

5.1. Mathematical Formulation

With input $X$ provided to the backbone $B$ in the network,

$$X_B = B(X)$$

$X_B$ is the activation output of the last layer of the backbone. As $X_B$ contains the common low level features of the image, to achieve improved results on the texture classification task, extracting texture features from $X_B$ and passing it to FC layers will help. Given that we are using $K$ different methods for TE. Each method is denoted as $M_i$ and output of any method $M_i$ will be written as,

$$X_{M_i} = M_i(X_B), \forall i \in [1, K]$$

There is an aggregation function $A$, which aggregates the output obtained from $K$ TE methods. Output of aggregation function can be formulated as,

$$X_A = A(X_{M_1}, X_{M_2}, \ldots, X_{M_i}, \ldots, X_{M_k})$$

$X_A$ will be passed as an input to the FC layer. In our paper $A$ is the concatenation function $CA$ which can be defined as,

$$CA(X_1, X_2, \ldots, X_i, \ldots, X_k) = X_1X_2 \ldots X_i \ldots X_k$$

Size of $X_{CA}$ can be defined as,

$$|X_{CA}| = |X_{M_1}| + \cdots + |X_{M_i}| + \cdots + |X_{M_k}|$$

**Bilinear models** The factors in bilinear models [10] keep the contributions of the two components balanced. Let $a^i$ and $b^j$ represent texture information of surface and spatial information with vectors of parameters and with dimensionality $I$ and $J$. Then the bilinear function $Y^{ij}$ is,

$$Y^{ij} = \sum_{i=1}^{I} \sum_{j=1}^{J} \omega_{ij} a^i b^j$$

where $\omega_{ij}$ is a learnable weight which balances the interaction between surface texture and spatial information.
The outer product notion captures a pairwise correlation between the surface texture encodings and spatial observation structures. Suppose \( A \) is the bilinear model \( BM \) then,

\[
|X_{BM}| = |X_{M1}| \times |X_{M2}|
\]  

### 5.2. Ensembling Texture Extraction Techniques

We propose an ensemble framework in which the selected TE methods should be unique in their working principle and should not have overlapping mechanisms. Failing on this aspect will result in less accuracy because of method similarity which provides overlapping features. To understand how using diverse techniques helps in improving accuracy, follow the Figure[1]. If we formulate this figure mathematically the equation becomes (ignoring bias term),

\[
Y_{H1} = X_{am1}^{1} \times w_{11}^{am1} + X_{am2}^{1} \times w_{12}^{am2} + X_{am1}^{2} \times w_{21}^{am1} + X_{am2}^{2} \times w_{22}^{am2} + X_{am1}^{3} \times w_{31}^{am1} + X_{am2}^{3} \times w_{32}^{am2} + X_{am1}^{i} \times w_{i1}^{am1} + X_{am2}^{i} \times w_{i2}^{am2}
\]

The above equation looks similar to a regression problem as formulated on the single hidden layer of the FC layer. To get better weights in this equation, correlation between the features should be as less as possible. In our case, to achieve less correlation, activation output from different methods should be less similar. It shows that diverse methods capturing distinct type of textures enable model to give better results. Feature extraction techniques are used after the convolution layers of backbone network, as shown in Figure[2]. After passing the input to the backbone network, the output from the final block is passed as an input to these unique TE methods. Several feature extraction strategies can be used as long as they are unique and distinct in extracting texture features. Before passing the outputs of the feature extractor to FC layers, the outputs from multiple texture feature extraction layers are concatenated. Lastly, the output from the FC layer is passed to a softmax layer to predict the output.

The framework discussed in Figure[2] is used as a model to produce SOTA results on known benchmark texture datasets. Three unique TE techniques are ensembled—DeepTEN [32], FAP [28], and Histogram Layer [22]. We are able to produce SOTA results for different datasets which will be discussed in the Results section. In further experimentation, other combinations of TE methods are considered, and based on the results it is observed that when GAP is not used, the accuracy of the model tends to increase. The architecture of our model is described in Figure[3] where output from the last block of backbone is passed to three separate feature extractors. 1) Downsampling layer followed by histogram layer, 2) Feature extractor is upsampled and passed to a fractal analysis pooling (FAP) layer, 3) Texture encoding layer passed to a normalization layer followed by FC layer. The upsampling and downsampling are done to match the input size between block 4 and FAP, and between block4 and histogram layer respectively.

In our architecture we have not included GAP technique unlike the most of the contemporary architectures. As seen in Table[1] when GAP is precluded while ensembling the other three techniques the accuracy increases with good percentage on FMD and KTH datasets on the contrary when GAP is combined with other three techniques then accuracy decreases. In the earlier methodologies, GAP is used to add the spatial information, however our research shows that for texture based networks GAP is not of much significance compared to the TE methods. As GAP captures the global spatial information of an image which does not
rely on the local features. However, texture patterns are
classified based on the local features. Thus, GAP is not of
much relevance in texture classification tasks. Though individ-
ual methods may produce good results, the combination of
unique techniques may offer a scope of improvement.

### 5.3. Bi-linear Pooling v/s Concatenation

BLP is utilized as the second-order interactions between
two inputs. One drawback of using second-order interac-
tion is it can accept only two inputs to participate, which
limits us from combining more than two inputs. Secondly,
provided that the same inputs are passed to BLP and con-
catenation, the output size of BLP is more when compared
to concatenation operation. Suppose that, value of $|X_{Mi}|$ as
per $2$ as $n \forall i \in [1, K]$, where $K$ is total number of methods
used. Comparing equation $5$ and $7$ we get, $|X_{CA}| = 2 \times m$
and $|X_{BM}| = m^2$ for $K = 2$. We can see that using con-
catenation aggregation function results in a linear increase
in the size of activation as the number of methods increase,
on the contrary applying bilinear pooling as an aggregation
function results in a polynomial increase in the activation
size as the number of methods increase. Due to the bigger
output size of BLP, the model becomes large and thus in-
creases the number of parameters. Thus, while combining
two TE techniques the output size in BLP will be greater
than or equal to concatenation i.e., $m + n \geq m + n$. Sec-
ondly, concatenation method can combine more than two
techniques at the same time. We can apply BLP for more
than two inputs, but it would not be explainable to make
second-order interaction between two inputs while leaving
other inputs as it is. Thus we prefer to use concatenation
rather than BLP in our proposed framework. BLP is not
a suitable method when more than two TE techniques are
used to extract features.

### 5.4. TE Techniques Selection

While ensembling the TE techniques diversity of meth-
ods is the key to enable optimal feature extraction across
and variety of input types. Also the distinct methods should
be compatible with the same backbone architecture. During
the selection of different TE techniques, we need to ensure
that the difference between the size of activation outputs is
not large, as it would impact the performance of the tech-
nique having smaller size activation output. For instance,
combining two techniques $A$ with an activation output of
size of 1024 and $B$ with an activation output size of 32 will
exert more importance on technique $A$ and thus dominating
method $B$. Pointwise convolution technique can be used to
reduce the activation output size to make it compatible to
use it with other techniques.

### 5.5. Selected Techniques and Hyperparameters

**Histogram** Used the implementation as per the paper
[22]. Output is taken from the last block of ResNet18. As
per the paper $dim$ is 2 for image data, $number$ of $bins$ is 4,
$bin$ width is 128 for ResNet18. The input size for the con-
volution layer is calculated by the formula,

$$\frac{feature\_maps}{feature\_map\_size \times number\_of\_bins}$$

which would be $512/(4 \times 4) = 32$ for ResNet18. The output
size of the convolution layer is calculated as a product of
the number of bins and the input size. In our case it is
$4 \times 32 = 128$ for ResNet18. For compatibility of the model
grouping is important, we set it as 512 groups.

**DeepTEN** Applied the DeepTEN technique as per
the paper [32]. The encoding layer accepts features or fea-
ture channels of dimension 512. The number of codewords
($n$ codes) used in our case is 8. Next is the linear layer with
input features as $512 \times n$ codes which is 4096 and output
features as 128. Lastly, batch normalization is done with
128 features.

**Fractal** Used FAP module as per the hyperparameter
settings and config in paper [28], with $dim$ value as 16.

**GAP** Global Average Pooling (GAP) is a pooling op-
eration designed to capture spatial information of an image
in classical CNN. We applied a 2D average pool over an in-
put signal composed of several input planes with the kernel
size 7. Added a linear layer to apply a linear transformation
to the incoming data with input features as 512 and output features as 48 followed by batch normalization.

5.6. Reasons to include Four Discussed Techniques

We have chosen DeepTEN [32], histogram layer [22], FAP [28], and GAP TE techniques for the proposed model design and experiments. Other methods such as DEPNet [29], DSRNet [30] and CLASSNet [6] are inherited from one of these used methods. Our choice of TE methods prevents any overlap in capturing the texture characteristics. The other existing methods leverage outputs from multi layers of the backbone network simultaneously; while our framework focuses on techniques applied to the backbone’s last layer output. Some techniques are not included due to similarity with above techniques. DEPNet and DSRNet use the same encoding layer that has been in DeepTEN. DSRNet [29] which was developed for ground terrain recognition uses the same texture encoding layer from DeepTEN. DSRNet has been built using ResNet50 [12] as a backbone but not uses ResNet18, but in our paper we have used ResNet18 [30]. Whereas, CLASSNet uses a concept of statistical self-similarity (SSS) [20] which is calculated with the help of fractals which is something similar to FAP. In CLASSNet the feature maps are learned using CNN and have a cross-layer SSS for exploiting the SSS of images. For the SSS-based texture recognition, fractal analysis is used to characterize the SSS on images [6]. The fractal analysis is also used in FAP for calculating the fractal dimension and classifying the texture based on the same.

Considering the other methods as just an extension of the already used methods or not used in the ResNet18 as backbone, we proceed to use the parent methods since we are ensembling the distinct techniques and we don’t want the texture to be categorized based on the same attributes more than once.

6. Comparison with Other Texture Extraction Techniques

Our proposed model concentrates on ensembling texture extractors with less correlation among them. We capture the unique texture characteristics of an image useful for classifying the images per their labels. GAP is a pooling layer and has the capability to be used in many techniques [11, 22, 28] to capture local-to-global spatial features, however as demonstrated it in not useful in TE techniques. The drawbacks of BLP v/s Concatenation are mentioned in section 5.3. With concatenation, we can preserve information from the previous layer in the same form. When there is minimal correlation between the characteristics extracted we can not afford to lose any information extracted by each of these techniques. For this reason concatenation is used to combine the DeepTen [32], Histogram layer [22] and FAP [28] to produce SOTA results on benchmark datasets such as KTH [5], FMD [25], and MINC.

In DeepTEN feature extraction, dictionary learning, and encoding representation training occurs simultaneously. The learned convolution features are easily transferred since the encoding layer learns an inherent dictionary that carries domain-specific information. DeepTEN is a flexible framework that allows an arbitrary input image size making it easier to combine with any model. FAP focuses on discriminating textures based on the fractal dimension i.e., based on the roughness of the texture. As mentioned earlier, histogram layer captures the texture information directly from the feature maps and is based on the fundamentals of local histograms which can be used to distinguish textures. All these techniques emphasize different texture characteristics for classification tasks thus ensembling these unique techniques enables elegant classification. When various characteristics are taken into consideration then our model has more rich information which helps to draw a more generalized boundary between distinct texture classes.

7. Experiment Evaluation

7.1. Experiment Setup

To test the effectiveness of our model we conduct the experiments on 6 benchmark datasets KTH [5], FMD [25], DTD [7], MINC [2], GTOS [33], and GTOS-M [29]. For FMD, DTD, MINC, GTOS, and GTOS-M we use the recommended data split plan. For KTH we generate 10 random splits in the ratio of 3:1 for train:test. The mean and standard deviation for the results are calculated for all the splits and presented in the table. ResNet-18 is used as a backbone and the model is trained using cross-entropy loss via an SGD optimizer and cosine scheduler for KTH, DTD, and GTOS. CosineAnnealing warm restart [18] scheduler is used for FMD, MINC, and GTOS-M. The model is trained for 30 epochs for DTD, FMD and KTH while for MINC, GTOS and GTOS-M the model is trained for 20 epochs. We use a batch size of 32 for KTH, 16 for FMD, 64 for DTD, MINC & GTOS and 128 for GTOS-M. Learning rate has been set to $1e^{-3}$ on FMD, $1e^{-2}$ on DTD, $5e^{-2}$ on GTOS-M and $5e^{-3}$ on KTH, MINC and GTOS. As part of the data augmentation the training dataset is transformed by resizing images into 256, random horizontal flipping, random cropping (five cropping technique for DTD and GTOS) of size 224, and finally by normalizing the images. The five crop augmentation method works well as texture is a neighborhood pixels based feature- cropping enriches the training data. It does not exhibit good results on MINC dataset because some shape based features are also present along texture based in this dataset. The model is built using Pytorch 1.7.1 version and the experiments presented here were run on NVIDIA DGX system with 8 x A100 32 GB GPUS.
Table 2. Comparing ensemble of three out of four techniques at once

| Dataset | DeepTEN | GAP | Histogram | FAP | Accuracy |
|---------|---------|-----|-----------|-----|----------|
| FMD     | Yes     | No  | No        | Yes | 82.0     |
|         | No      | Yes | Yes       | Yes | 80.7     |
|         | Yes     | No  | Yes       | No  | 83.1     |
|         | Yes     | Yes | No        | Yes | 81.9     |
|         | Yes     | Yes | Yes       | No  | 82.2     |
| KTH     | Yes     | Yes | Yes       | Yes | 86.7     |
|         | No      | Yes | Yes       | Yes | 86.4     |
|         | Yes     | No  | Yes       | Yes | 88.04    |
|         | Yes     | Yes | No        | Yes | 87.1     |
|         | Yes     | Yes | Yes       | No  | 87.8     |

Table 3. Comparing ensemble of two out of four techniques at once

| Dataset | DeepTEN | GAP | Histogram | FAP | Accuracy |
|---------|---------|-----|-----------|-----|----------|
| FMD     | Yes     | Yes | No        | No  | 82.7     |
|         | No      | Yes | No        | Yes | 81.9     |
|         | Yes     | No  | Yes       | Yes | 82.3     |
|         | No      | No  | Yes       | Yes | 52.8     |
|         | No      | Yes | Yes       | No  | 80.2     |
|         | No      | Yes | No        | Yes | 77.4     |

Table 4. Mean accuracy of each technique applied individually on FMD and KTH

| Method    | FMD     | KTH     |
|-----------|---------|---------|
| DeepTEN   | 80.0    | 86.245  |
| GAP       | 79.4    | 85.62   |
| HISTOGRAM | 72.9    | 86.027  |
| FAP       | 33.8    | 60.52   |

7.2. Results

On comparing our proposed model with well-known texture-based classification models CLASSNet [6], DeepTEN [32], DSRNet [29], MAPNet [31], LSCNet [4], DEPNet [29], HistNet [22], and FENet, the results obtained are presented in Table 5. The results for TE methods used for comparison have been quoted directly from the respective papers and left blank where corresponding results are not available. Our method gives SOTA accuracy for FMD, KTH, and MINC for the ResNet18 backbone. Standard deviation for KTH is higher due to the randomness in the splitting of the data. In comparison to the other methods, our model increases the accuracy on benchmark datasets by a significant percentage. We also produce notable results for DTD, GTOS, and GTOS-M datasets. For GTOS our model is only behind the CLASSNet reported accuracy. Apart from accuracy metric, our architecture is more efficient compared to the current models in terms of the training time. Currently our proposed model takes less time to train large datasets such as MINC, GTOS, GTOS-M producing the model’s best accuracy within 20 epochs of training with similar batch sizes as used in published papers. We conducted additional analysis on the ensemble methods. This was to study the TE technique performance when used alone, in combination of two techniques, and in combination of three techniques. The results for ensembling three techniques at the same time can be seen in Table 2 for FMD and KTH dataset. Table 3 depicts the results for two techniques on FMD dataset. Table 4 demonstrates how each technique uniquely performs on FMD.

7.3. Effectiveness of Proposed Ensemble Technique

Our proposed ensemble technique outperforms published research on models which have shown SOTA results on texture-based classification. Our technique works on the principle of combining diverse techniques to produce a better result than any other technique used alone. Various combinations were researched and experimented on as part of this work as can be seen from Tables 2, 3, and 4. It turns out that the combination of DeepTEN, FAP, and Histogram performs extremely well on all 6 benchmark datasets. We produce new SOTA results on KTH, FMD, and MINC dataset. The more general way to look at this framework is to combine as many effective methods as possible for the classification task. However, When all the four methods were ensembled, we observe a dip in the accuracy in contrast to the combination of only three methods. This suggests that more investigation is needed in selecting the techniques to be used in the ensemble. The general rule is to combine techniques together which have different working principles. Suppose a Model A individually gives the correct prediction on a certain image while Model B individually gives a wrong prediction on the same image, when combined together in an ensemble, the network design changes and the model weights would result in either correct prediction or a wrong prediction. Thus the combination of methods should be properly investigated before ensembling is employed.

7.4. More Analysis

For the four techniques considered—FAP, GAP, DeepTEN, and HISTOGRAM, we tried experimenting with various possible combinations as per Tables 2, 3, and 4. Total number of these experiments is 15 on single dataset FMD. As shown in Table 2, the highest accuracy obtained on FMD-related experiments is 83.10 by combining the three techniques DeepTEN, Histogram, and FAP. The peak accuracy for the combination of two methods—GAP and DeepTEN is 82.7, whereas, the peak accuracy for a single method (DeepTEN) is 80.0. We can observe that DeepTEN plays a major role in attaining the highest accuracy in every combination. In the three out of four methods combination experiment, if we remove DeepTEN the accuracy dropped to 80.7 which clearly demonstrates the impor-
Table 5. Classification accuracies (%) in the form of "mean±s.t.d." on the ResNet18 backbone. Best results are boldfaced

| Method | FMD     | KTH     | DTD     | MINC    | GTOS    | GTOS-M  |
|--------|---------|---------|---------|---------|---------|---------|
| DeepTEN| -       | -       | -       | -       | -       | 76.12   |
| DEPNet | -       | -       | -       | -       | -       | 82.18   |
| DSRNET | 81.3 ± 0.8 | 81.8 ± 1.6 | 71.2 ± 0.7 | -       | 81.0 ± 2.1 | 83.65 ± 1.5 |
| MAPNET | 80.8 ± 1.0 | 80.9 ± 1.8 | 69.5 ± 0.8 | -       | 80.3 ± 2.6 | 82.98 ± 1.6 |
| LSCNET | 76.3 ± 0.1 | -       | -       | -       | -       | -       |
| FENET  | 82.3 ± 0.3 | 86.6 ± 0.1 | 69.59 ± 0.04 | 80.57 ± 0.10 | 83.10 ± 0.23 | 85.10 ± 0.36 |
| HistNet| -       | -       | -       | -       | -       | 79.75 ± 0.8 |
| CLASSNET | 82.5 ± 0.7 | 85.4 ± 1.1 | 71.5 ± 0.4 | 80.5 ± 0.6 | 84.3 ± 2.2 | 85.25 ± 1.3 |
| Ours   | 83.10 ± 0.83 | 88.047 ± 3.45 | 70.208 ± 1.01 | 80.80 ± 0.44 | 83.38 ± 1.85 | 83.56 ± 0.0 |

Figure 4. Importance of techniques in deciding the accuracy

in given experiment as 1 while absence as 0. We implemented Random Forest Regression algorithm on the formulated problem and calculated the feature importance on the trained model. We obtained the Figure 4 by this procedure. It suggests, GAP has higher feature importance. In our case, it communicates that adding GAP tends to reduce the accuracy, on the contrary, removing GAP increases the accuracy. This is not always the case, for our model adding GAP can produce better results for datasets like GTOS & GTOS-M. Furthermore, DeepTEN has the second highest feature importance value, which conveys that adding DeepTEN helps in increasing the accuracy while removing it reduces the accuracy values in context of our experimental setup. Histogram and FENet have the third and the least feature importance values respectively.

8. Conclusion

In summary, we propose a novel approach combining diverse TE techniques for improved learning compared to when these techniques are used individually. We develop a framework that incorporates two or more texture-related techniques in a scalable way and demonstrate its effectiveness on benchmark texture datasets. The suggested framework not only delivers SOTA results but helps explain the impact of using dissimilar techniques in combination. We also produce better results on the larger datasets e.g. MINC, GTOS, and GTOS-M in less number of epochs i.e., 20 epochs as compared to 30 epochs in the cited papers covering various techniques.

Our innovation offers an experimentally-proven combination of the existing texture extraction methods, efficiently, in terms of training steps and no. of parameters, eliminates the complexity of manual method selection and dependency on the training dataset. Our novelty is in research and presentation of a holistic architecture for extraction of diverse Texture patterns from images. With almost same number of parameters this approach produces SOTA results on 3 datasets in only 20 epochs as compared to 30 epochs in all
the other cited methods. None of the previous research work covers the all listed benchmark texture datasets demonstrating results equally well across all.

In table 2 and 3 of the paper, we prove that using a random combination of the existing techniques does not produce SOTA results, therefore, the novel framework with its embedded specific texture extraction techniques proposed is non trivial.

We present our analysis on importance of GAP with respect to texture-based image datasets and discover that GAP does not exhibit significance for texture classification. In this paper, ensemble methods produce an improved results as compared to individual methods. Our ensemble architecture is simple and can easily be employed in standard CNNs as well as complex CNN architectures. We combined three very different TE methods- DeepTEN, wherein feature extraction, dictionary learning, and encoding representation- all happen at the same time, FAP which focuses on discriminating textures based on the fractal dimension, and the histogram layer which captures the texture information directly from feature maps, via local histograms. Thus, it is up to the practitioners to try and use suitable TE method combinations to make a model perform well on other datasets.

We have considered 6 popular benchmark texture datasets to show the effectiveness of the proposed approach and achieved SOTA results on FMD, KTH, and Minc in this work. For the other 3 datasets our results are comparable with current SOTA results, achieving optimal results within 20 epochs of training. Our ensemble is scalable- other techniques can be added and existing ones can be removed from the existing architecture to experiment with other datasets. Our future work will entail investigating which TE methods to select while combining unique feature extractors based on the texture types of the given dataset with the goal of improving outcomes.

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