Data Preprocessing Technique for Neural Networks Based on Image Represented by a Fuzzy Function

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***Abstract*—Recently further developed Deep Neural Network sheds light on automatically learning high-level image representation from raw pixels. Deep learning with Convolutional Neural Networks has shown great promise in image-based classification and enhancement but is often unsuitable for predictive modeling using features without spatial correlations. We present a feature representation approach to arrange high dimensional vectors in a compact image form conducible for CNN-based deep learning. This paper demonstrates the use of deep neural networks for developing a system that can recognize various texture features.**

Keywords*—*Deep Neural Network; CNN; Image representation by a Fuzzy Function; Image Classification.

I. INTRODUCTION

Texture is a key component used for various applications in computer graphics. While its definition varies slightly, texture is typically a surface image of an object and it does not represent the shape of object. For example, a photograph of an entire human face is usually not considered to be texture, but a close-up of a human skin is. In rendering, artists use textures to add surface details to objects without having to increase geometric complexity. For image processing, texture is used to represent types of surfaces that are independent of shape. Texture can be thought as a basic element that captures the appearance of surfaces of objects. Accurate classification of textures is also fundamental in many important applications such as inspection and segmentation for image processing and generation of texture database for rendering. At the same time, texture feature representation is a challenging problem since textures often vary a lot within the same class, due to changes in viewpoints, scales, lighting configurations, etc. In addition, textures usually do not contain enough information regarding the shape of objects which are informative to distinguish different objects in image classification tasks. Due to such difficulties, even the latest approaches based on convolutional neural networks achieved a limited success, when compared to other tasks such as image classification. We propose a unification of two major classification approaches, convolutional neural networks and spectral analyses, to approach the difficulty of texture feature representation.

In the last three years, mainly due to the advances of deep learning, more concretely convolutional networks, the quality of image recognition and object detection has been progressing at a dramatic pace. One encouraging news is that most of this progress is not just the result of more powerful hardware, larger datasets and bigger models, but mainly a consequence of new ideas, algorithms and improved network architectures.

The main idea of the Inception architecture is based on finding out how an optimal local sparse structure in a convolutional vision network can be approximated and covered by readily available dense components. Note that assuming translation invariance means that our network will be built from Convolutional building blocks. All we need is to find the optimal local construction and to repeat it spatially. Arora et al. suggests a layer-by layer construction in which one should analyze the correlation statistics of the last layer and cluster them into groups of units with high correlation. These clusters form the units of the next layer and are connected to the units in the previous layer. We assume that each unit from the earlier layer corresponds to some region of the input image and these units are grouped into filter banks. In the lower layers (the ones close to the input) correlated units would concentrate in local regions. This means, we would end up with a lot of clusters concentrated in a single region and they can be covered by a layer of1×1convolutions in the next layer, as suggested in [12]. However, one can also expect that there will be a smaller number of more spatially spread out clusters that can be covered by convolutions over larger patches, and there will be a decreasing number of patches over larger and larger regions. In order to avoid patch-alignment issues, current incarnations of the Inception architecture are restricted to filter sizes1×1,3×3and5×5, however this decision was based more on convenience rather than necessity. It also means that the suggested architecture is a combination of all those layers with their output filter banks concatenated into a single output vector forming the input of the next stage. Additionally, since pooling operations have been essential for the success in current state of the art convolutional networks, it suggests that adding an alternative parallel pooling path in each such stage should have additional beneficial effect, too

Deep neural network based Convolutional neural networks (CNNs) process an input textures-is and collect statistics in the spatial domain. Spectral analysis transforms an input texture into a spectral domain and uses frequency statistics. CNNs are usually good at capturing spatial features, while a spectral analysis is good at capturing scale invariant features. We aim to consider both the spatial and spectral information so that it captures both types of features well under a single model. The key idea is that the pooling layer and the convolution layer in CNNs can be thought as a limited form of a spectral analysis. Based on this idea, we generalize both layers to perform a spectral analysis using multi resolution analysis by wavelet transform. We thus named our model as wavelet convolutional neural networks (wavelet CNNs). The overview of wavelet CNNs is shown in our model is thus easier to train and consumes less memory than CNNs. To summarize, our contributions are: Combination of CNNs and spectral analysis using Google net. Accurate and efficient texture feature representation using our model. Several numerical experiments in the results section validate that our model successfully classified failure cases of existing models.

Fuzzy image processing is special in terms of its relation to other computer vision techniques. It is not a solution for a special task, but rather describes a new class of image processing techniques. It provides new methodology, augmenting classical logic, a component of any computer vision tool. A new type of image understanding and treatment has to be developed. Fuzzy image processing can be a single image processing routine, or complement parts of a complex image processing chain.

II. LITERATURESURVEY

1. Apostolos Chondronasios1 · Ivan Popov1 · Ivan Jordanov1 (2015) et al

A computer-based vision method has been developed in this paper to inspect surface defects on aluminum profiles. Two faults, blisters and scratches were studied and divided into three groups the analysis (non-defective, blister, scratch). For this application, we carried out a feature selection which resulted in 98.6 percent precision with only two features. The high precision of detection combines the existing field literature with a new approach to variables, such as choosing and modifying Values from the co-occurrence matrix statistical characteristics of the Sobel operator gradient magnitude of the image. We have dubbed this matrix GOCM to differentiate it from standard approaches to GLCM to GLGCM. Although the aluminum surface texture is almost stochastic, making it extremely difficult to detect flaws, we have shown that using GOCM statistical features is more acceptable for extruded aluminum surface inspection. More examples of various defect forms such as dialing, picking up, breaking, stamping coauthors, welding lines and black lines can be added to further enhance the analysis. The accuracy is predicted to fall with the detection of further defects when only two characteristics are used so they are losing their ability to discriminate. The details can be best distinguished from related faults using different types of Cameras and Measurement Devices. Future study is also possible to assess the performance of various classification schemes, for example vector supporters and to compare them with performance of neural networks. Last but not least important path in future research is the checking by means of regular texture benchmarks of the suggested GOCM methodology.

2. MyeongAh Cho , Graduate Student Member, IEEE, Taeoh Kim , Graduate Student Member, IEEE, Ig-Jae Kim , Member, IEEE, Kyungjae Lee , Member, IEEE, and Sangyoun Lee , Member, IEEE(2021) et al

The Relative Graph Module (RGM) derives relative knowledge of each identity by integration into a node vector of any face variable and models the relationships between them. A hierarchical methodology focused on extracting relationships solved the problem of divergence between HFR domains. In addition, by plugging in a pre-trained face extractor and fine tuning, the RGM resolved the issue of the lack of suitable HFR databases. Moreover, the node-wise recalibration was done through the Node Attention Unit (NAU) to concentrate on global informative nodes between propagated node vectors. Author's new C-softmax loss has helped to adjust traditional projection spaces by increasing the level of similarity. We also applied the RGM module to a number of pre-trained backgrounds and examined improved results on NIR-to-VIS and Sketch-to-VIS projects. In addition, each proposed approach demonstrated its effect by improved success in ablation studies. Moreover, the visualization, in VIS, NIR, and sketch pictures, of relational knowledge revealed that relationships within the face are identical in each field, showing representative field invariant characteristics. Author's methodology was even stronger than the advanced CASIA NIR-VIS 2.0, IIIT-D Sketch, BUAA-VisNir, Oulu-CASIA NIR-VIS and TUFTS approaches.

3. Z. Chen, R. R. Derakhshani, C. Halmen, and J. T. Kevern et al

The author used the DSLR macro light camera. The perpendicular and angled lighting is used for 11 specimens containing light and mildly broken concrete surfaces. The textural characteristics derived from data on gray level co-occurrence matrixes, from which 3-6 characteristics were chosen. Accuracies of cross-validation with neural network classifier have been as high as 94 per cent, suggesting the feasibility of fast, automated beta cracking evaluation with COTS digital imagery.

4. Lin Chen1, MengYang (2016) et al

This paper suggested a semi-supervised paradigm for discriminatory dictionary analysis. By combining mark distribution with the class-specific reconstruction error of each unlabeled sample, the class of unlabeled samples can be calculated to train Authors model more accurately. The differential property of branded training data is also well discussed by using the concept of segregation and reducing the scatter of the coefficients in the classroom. Several trials, including face-recognition simulations, digital recognition and texture classification, demonstrate Authors method's superiority over supervised and other semi-supervised approaches to dictionary learning. More questions of classification may be discussed in future, for example where the samples in training do not belong to any recognized class.

5. Kaveri Chatra1 · Venkatanareshbabu Kuppili1 · Damodar Reddy Edla1 (2019) et al

This paper suggests a new approach for the classification of texture images called BDADNN. Based on the health function of binary dragon flies based on the deep neural network. We begin with a two-level threshold to decompose gray images into a number of binary images. We measure fractal dimensions for the capturing of binary image boundary complexities and derive GLCM and GLRLM matrices features to capture the spatial pixels dependences in the gray image. Fusion of fractal dimensional characteristics and GLCM and GLRLM are also a best solution. However, we chose a naturally influenced algorithm called the Binary Dragonfly Algorithm, with a new function for the collection of features, to reduce its high dimensionality. In order to optimize deep neural network and importance and minimize the amount of characteristic features of input data, the suggested fitness function of the binary dragonfly Algorithm is formulated. Authors suggested approach has been experimented. Different groups are used to experimental assessment for two well-known texture image datasets called textured surfaces and KTH-TIPS. Cross validation methodology is employed to consider the classification efficiency impact of the training dataset in scale. The suggested solution performance assessment is compared to the SVM. In terms of correct labeling, the proposed procedure exceeds SVM. There is also a high statistical importance of the rise in classification accuracy.

6. Hyun Sung Chang, Member, IEEE, and Kyeongok Kang (2005) et al

In this article, we introduced a new algorithm that was useful in a broad range of applications to detect and identify edge components in block levels [7],[8],[14],[16]. This scheme, derived systematically from a pixel domain algorithm, performs with minimal arithmetical operations on the DCT coefficient domain (especially multiplications). Although, as outlined in Sections IV and V, the proposed approach also applies to moving images without significantly increasing complexity, it can also be used for effective video analyses, such as scene recognition and classification. This is one of Authors constant research topics.

7. Akarsh Aggarwal, Anuj Rani, Manoj Kumar (2019) et al

The paper suggests a new technique, which uses gray-scale graphics and a location histogram, for horizontal and vertical edge processing and segmentation to extract ably detect the desired ROI. Author's data collection, which includes different lighting conditions, different distances and resolution, is used for experimental evaluation of Authors algorithm. The outcome is highly successful when applying the work recommended and provides a detection rate of 93.34 percent for vehicle licensing plates. This illustrates the applicability of the proposed work to classify license plates. Methods are therefore vulnerable to different variables, such as broken license plates, tags, stamps placed on the car's body parts and which degrade the detection rate, including the location, personal appearance and exterior factors. We can solve these problems by different techniques of image processing consisting of histogram equalization, dynamic range imaging (HDR). Some issues, such as image rotation number plate identification, must be resolved in the future.

III. PROPOSED METHODOLOGY

Texture representation, i.e., the extraction of features that describe texture information, is at the core of texture analysis.

As a classical pattern recognition problem, texture classification primarily consists of two critical sub problems: texture representation and classification. It is generally agreed that the extraction of powerful texture features plays a relatively more important role, since if poor features are used even the best classifier will fail to achieve good results.

Image classification means assigning the label to input image from fixed set of categories. The image classification includes variety of application like designing robots, objects identifications, automatic cars, traffic signal processing. Feature extraction is more important task for the image representation in classification problem. DNN applied on large-scale datasets to learn images representation and reuse it for the classification.

Objective of this paper is to apply convolutional neural network for image classification problem. DNN architecture are proposed. To test the performance of CNN we have used Google net.

The main objective of convolutional layer is to obtain the features of an image by sliding smaller matrix (kernel or filter) over the entire image and generate the feature maps. The pooling layer used to retain the most important aspect by reducing the feature maps. Fully connected layer interconnect every neuron in the layer to the neurons from the previous and next layer, to take the matrix inputs from the previous layers and flatten it to pass on to the output layer, which will make the prediction.

In recent years, machine learning (ML) has produced numerous insights from the surge of data generated in diverse areas. In computer science, the representation of an image can take many forms. Most of the time, it refers to the way that the conveyed information, such as color, is coded digitally and how the image is stored, i.e., how is structured an image file. Several open or patented standards were proposed to create, manipulate store and exchange digital images. They describe the format of image files, the algorithms of image encoding such as compression as well as the format of additional information often called metadata. Differently, the visual content of the image can also take part in its representation.

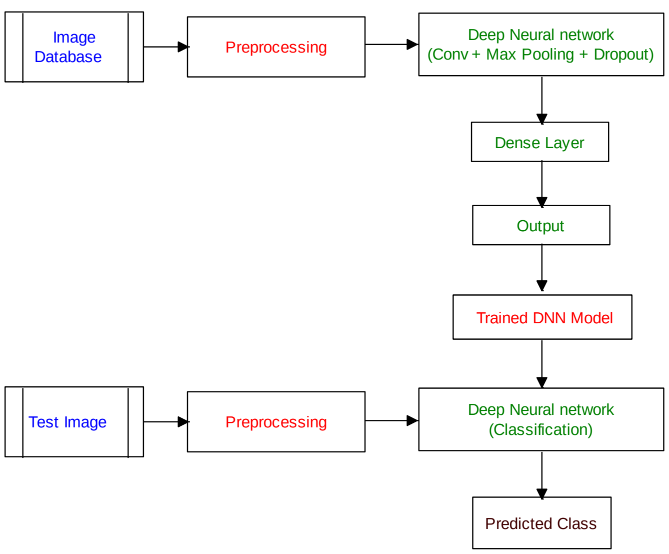

Figure: System Architecture

Mathematical Model:

- **System Description:**

S= {I, F, O}

INPUT:

- F=F1,F2,F3...FN Function to execute result
- **I**=C1,C2,C3... input of systems outfit images
- **O**=R1,R2Rn
- I=Result access by User
- C1=Texture Feature Representation

F:

F1=Image processing applied on natural texture

F2=feature extraction from images

O:

R1= model creation from training.

R2= model based image testing

SPACE COMPLEXITY:

The space complexity depends on Presentation and visualization of discovered patterns. More the storage of data more is the space complexity.

TIME COMPLEXITY:

We are going to use Google net for fast and better recognition with higher accuracy. So time complexity is less. So the time complexity of this algorithm is $O(n^n)$.

Success:

1. High accuracy achieved by using all type of image dataset.
2. User gets result very fast according to their needs.

Failures:

1. Huge database can lead to more time consumption to get the information.
2. Hardware failure.
3. Software failure.

Mathematical Model in Equation format

Notation

Where,

- M= Set of all entities.
- T1= Natural Texture Images data
- T2= Texture Feature classification
- TN= Texture Feature Representation images type N

HDI=Total images dataset

A Neuro-Fuzzy Function:

A Neuro-Fuzzy Function is a fuzzy system that uses a learning algorithm derived from or inspired by neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing Texture Image. Neuro-fuzzy Function which explain in more detail below.

Modern neuro-fuzzy Function are usually represented as special multilayer feed forward neural networks (see for example models like ANFIS [13], FuNe [12], Fuzzy RuleNet [16], GARIC [8], or NEFCLASS and NEFCON [14]). However, fuzzifications of other neural network architectures are also considered, for example self-organizing feature maps [9, 17]. In those neuro--fuzzy networks, connection weights and propagation and activation functions differ from common neural networks. Although there are a lot of different approaches [10, 11, 14, 15], we usually use the term neuro-fuzzy Function for approaches which display the following properties:

A Neuro-Fuzzy Function depends on a fuzzy machine that has been trained using a neural network-based learning algorithm. The learning procedure works on local knowledge and results in only small variations to the overall fuzzy structure.

A Neuro-Fuzzy Feature is a three-layer feed forward neural network. The first layer represents the pixels in the input image, the middle (hidden) layer represents the fuzzy law, and the third layer reflects the texture representation. (Fuzzy) relation weights are used to encrypt fuzzy sets. To introduce a supervised learning to a fuzzy inference system, this is not appropriate to interpret it in this manner. It may, furthermore, be useful since it reflects the data flow of information processing and training within the system. A 5-layer structure is often used, with the fuzzy sets defined in the units of both the second and fourth layers.

IV. CONCLUSION

We will be using this method for the challenge of picture Representation and classification, a DNN based CNN using Fuzzy logic. It proposes DNN architecture. We utilized MNIST datasets to assess the performance of CNN. The basic goal of a dense layer is to get the picture's features by sliding the little matrix across the whole image (kernel or filter) and to create the maps. By decreasing the function mappings, the pooling layer retained the most significant aspect. The fully connections of the layer connect each neurons in the layer to the neurons in the preceding layer and the next one, taking input matrices from the preceding layers.

Future work will be based on the various texture representation and its result comparison.

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