A Survey of Image Classification Methods

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Abstract — Image classification is a complex field in image processing as noisy and blurry images are more difficult to classify. There are many techniques for classification and removal of noise however, these methods does not provide classification accuracy. In this article, analysis on problems, trends and factors and their effects on image classification is discussed. The basic purpose of this survey is to provide brief overview of image classification techniques. This survey will help the readers who wants to know about current image classification techniques. Convolutional neural network (CNN) is the one of most popular deep neural network technique. CNN gives better performance and improve classification accuracy.

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Keywords—Image Classification, convolutional networks, Semi-supervised learning.

I. INTRODUCTION

In the modern era, computers become more efficient and smart because of Artificial Intelligence. AI have many types; Machine learning is one of them. Furthermore, machine learning also have many techniques which are shown in figure.1. These techniques are used to arrange the data sets. [1]

1) Supervised learning: In the supervised learning, data sets are trained according the models. To train the data sets some algorithms are used which maintain the inputs of data. In supervised learning classification and regression are the main types.

Classification: It gives the prediction of Yes or No, for example, “Are you coming to university?”, “Does this university meet to its standards?” Regression: “How much” and “How many” comes into regression.

2) Unsupervised learning: In supervised learning targets are not available. This technique is used to find out the similarity between the input data and analyzed data. This technique is also used for data analysis. It’s also calls density evaluation. Unsupervised learning is often used to pre-process the data. clustering comes into unsupervised learning. Clustering: On the basis of similarity it makes clusters.

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3) Semi supervised learning: It’s a sub-type of supervised learning. Because in this technique unlabeled and labeled data can be used. This type of data lies between supervised and unsupervised learning that’s why it’s called semi-supervised learning.

4) Reinforcement learning: This learning is created by using a field of psychology. This learning is used when we don’t know about the answers then an algorithm is enlightened but, still it does not notify the methods to correct the problem. To find the correct method for the problem It has to check and test various methods. Observer learning is another name for this learning. However, it does not help to informed about progress. This learning is different from other learning as we don’t know about the correct input and output information.

5) Evolutionary learning: This learning includes biological development in which biological organisms are taken and modified to make development for their continuity. To check the accurate answer this learning is used in modeling of computer.

6) Deep learning: Algorithms are used in this branch of machine learning. It uses tree like graph which includes different processing layer, which made different linear and non-linear modifications.

Nowadays deep learning is very popular research topic, and CNN is the prominent model for image classification, image clustering and image recognition. CNN is said as a new technique for both image classification and image recognition because it gives high accuracy. [2] CNN show the durable component representation in computer vision. CNN finds the pattern of the image, first few layers are used to identify lines and corners, this pattern then pass through CNN and recognize more complex features as we get deeper. This property of CNN makes good at identifying objects in image. CNN gives better performance and improve classification accuracy. Classification process shown in figure 2.

Section I consists of introduction of paper. The image classification methods are discussed in section II. Convolutional neural network, is discussed in section III. Section IV consists of open issues. Section V consists of conclusion of the paper.

A. Background

Deep learning is new area of study of machine learning. Architecture of deep learning is as deep belief networks, deep neural networks and recurrent neural network applied on different areas like speech recognition, computer vision, audio recognition, natural language processing machine translation etc., which gives high accuracy. [3]

CNN is proposed in 1988 and its planning is same as Artificial Intelligence. It is used in pattern recognition problems like speech recognition, image classification etc. CNN consists of

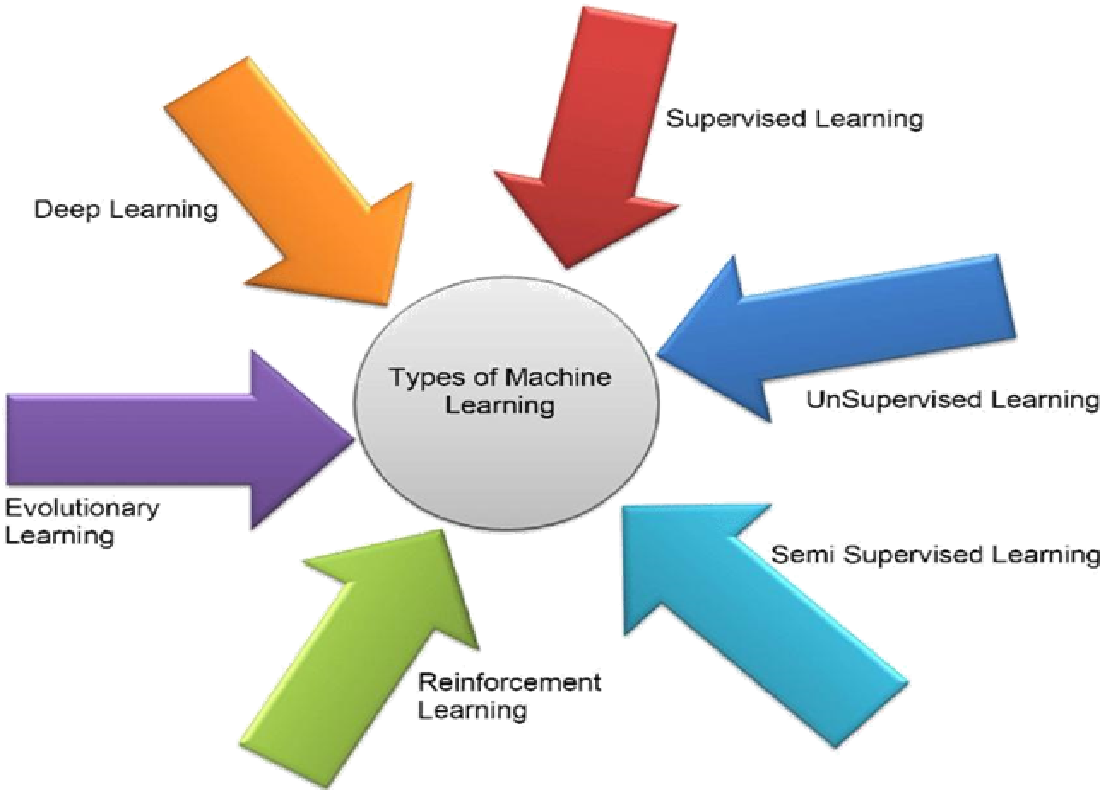

Figure 1 Type of Machine Learning

B.Motivation

In this [4], deep CNN features are used for classification of land-use scene. To extract the features of CNN two simple and effective approaches (1) For feature extraction pre-trained CNN models are being used. (2) Domain-specifically pre-trained CNN models on domain specifically classification data sets are used. Author in [5], propose a detection technique using Selective Search and CNN for character faces. In [6], by using different images and created annotation data recognized by the panel layouts by using faster R-CNN are shown. In this article [7], proposed an algorithm based on feature fusion hyper spectral and LiDAR fused classification. It takes the two set of features and two kinds of data sets. Both are used to enhanced the classification effect. In [8], novel cross-domain CNN is used which improves the classification accuracy. This proposed technique, trained with the multiple data sets which give better accuracy than the individually training case. By getting the motivation from these articles, we use CNN for image classification. For CNN, we use CIFAR1 data set.

II. RELATED WORK

In this section related work is discussed.

A. Image Classification Methods

In [9], author, enhanced the classification performance over the shallower network. In this paper author proposed a fully CNN with nine layers, which are deeper than other convolutional networks. Residual learning used for learning efficiency. For the multi scale fillers spatio-spectral interactions used which consists of three convolutional filters. By using the CNN architecture, the proposed technique is performed on three different data sets to check the efficiency of technique and to enhanced the performance: 1) deep network with improved training and 2) spatio-spectral information.

Author in [10], solve the data set scarcity issue and improve the classification accuracy by proposing a technique cross domain CNN. It performs hyper spectral image classification for multiple classification. Proposed technique is perform well on multiple data sets than the single data set.

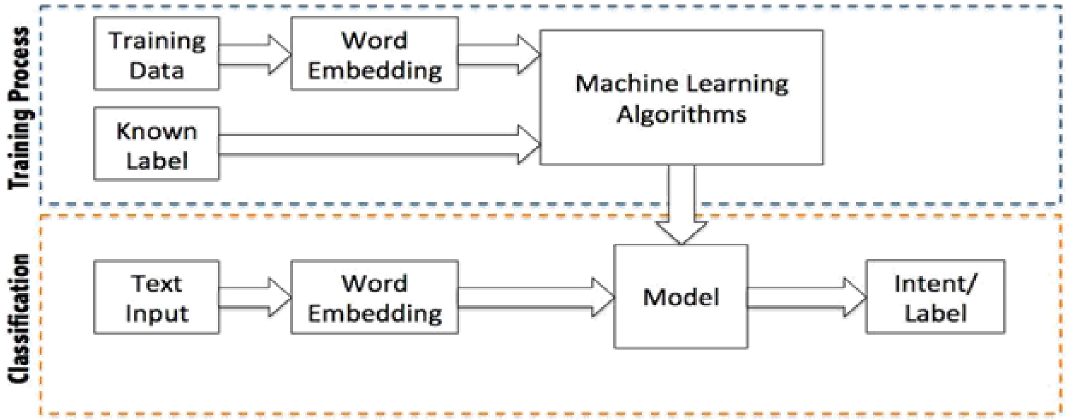

Figure. 2: Classification and training process

prove that by using shared layers across the domain improves the classification accuracy.

In [11], proposed a deep CNN technique for scene classification and Used the two approaches for CNN features extraction: (1) as a universe feature extractor use pre-trained CNN (2) for our classification data set pre-trained CNN model is use. For scene classification a new classifier SVM is used. It performs on publicly available data set and results proved that for scene classification deep CNN is effective.

In [12], proposed a model named Wishart auto encoder (WAE) for classification of polarimetric synthetic aperture radar (POLSAR) images. To improve the classification result author combined this classification model and clustering idea. In some techniques K-means and AE network are used to improve the performance, author used the WAE and K-means for making the clustering-WAE network. To complete the classification task, clustering-WAE network is connected with softmax classifier. Through experiments, it concluded that proposed technique is effective. Clustering-WAE network performs the remarkable classification performance then the other algorithms.

In [13], there is no super pixel designed for image classification specially. In this paper author proposed a technique fuzzy super pixel to minimize the generation of mixed super-pixels. Mixed super-pixels cause bad effect on performance. Fuzzy super-pixels designed for less mixed super-pixels. In this paper, not all pixels allocated to corresponding super pixels. Second, proposed a new algorithm, fuzzyS (FS) for Pol-SAR image classification. To verify the effect of FS, three pol-SAR images are used. Different experiments are done to prove the performance of FS algorithm however, performance of fuzzy super-pixels improved through well-designed classification process.

In [14], author used the image fusion technique to improve the classification accuracy. Spatial and spectral resolutions pro-vide the better information about image. Image fusion through the principal component analysis (PCA), multiplicative and the brovery. Resultant image classified by using supervised classification. Performance of Brovery is 99.67, PCA is 98.63 and multiplicative 98.71. However fusion image gives better result than the original image. In [15], to perform the hyper spectral image classification, author proposed an iterative sup-port vector machine (ISVM), iterative version of SVM. Firstly, original image is taken and through its principle components form the hyper spectral data cube, then initial classification map is produced by applying SVM. Gaussian filter is applied to get the spatial information of SVM classification map and for the next round of iteration combine with currently processed hyper spectral cube. ISVM compare with other technique to evaluate the performance. Through experiments it shows that, it provides high classification accuracy.

Author in [16], proposed a deep network by using CNN for classification of synthetic aperture radar (SAR) target classification. Further two stages: classification sub network and de speckling sub network is proposed to differentiate multiple categories. For training the data noised SAR images is being used. Firstly, reduce the noise by applying de speckling sub-network and then through classification sub network, residual speckle features and target information is learned, which solves the noise problem of CNN. By using MASTER Data set, results shows that classification accuracy is higher than 82% at different noise levels.

In [17], a hyper spectral and LiDAR combined classification technique proposed which based on feature fusion. Fusion of two set of feature and two types of data prominently enhance the effect of classification. On MUUFL Gulfport, data set shows the good result. Through experiment classification, accuracy is 82 %.

In [18] author Proposed a technique based on decision tree to recognize and classify the different kinds of images. Classification is needed for the image processing first and convert these images into color categories (gray scale, RGB and YCbCr). This method is automatic without interference of user who does not know any knowledge to operate the image classification. Proposed technique is tested on 400 images and author was succeed to achieve 92% accuracy.

In this article [19], proposed a technique curriculum learning method for improve the quality of semi-supervised classification. Images from different features are gathered and combined on curriculum learning sequence (sequence: classifying unlabeled images) generated simple to difficult form. Five semi-supervised classifiers is used for comparison with other techniques. Eight different data sets are uses for experiments. Through experiments, the accuracy of semi supervised image classification is explained. This technique also relevant to other semi-supervised classification problems.

In [20], this article, proposed a deep learning approach CNN for image categorization between abnormal and normal images of optical coherence tomography (OCT). Different layers of network are used to extract features. Classification are performed on basics of different classifiers e.g., random forest, KNN etc. and results give 90% accuracy and improve the performance 20% more as compare to another research. Data set is taken from Singapore eye research institute (SERI). In this paper [21], authors proposed a spatially constrained (BOV) method for image classification. In that model, two types of features are used. The image representation in BOV based on statistics of occurrence of visual words for each patch. This technique is compared to many other new methods.

In this paper [22], authors used a patch-based approach that captures spectral information and structural information for extracting descriptors. This approach leads to a classification scene which assist us to search for new and previously launched satellite missiles.

In this paper [23], they proposed an algorithm which uses images for computer aided detection (CADe), which uses the region switch CNN features for the observation of lungs symptoms such as diffuse lung diseases and lung modules.

In this paper [24], authors addressed a problem of hand-crafted features. Most of the algorithms does not take into inter-relationships between color information and intensity. They addressed this problem with quaternion representation for color images. By using this algorithm, they were able to encode the intensity and color information of an image and merges as a variable to both handcraft representation and convolutional neural network.

In [25], authors proposed an algorithm whole-slide image color standardize (WSICS), which uses color and structural information for the classification of pixels into different components. Performance of this algorithm evaluated by two data sets. This algorithm improved the accuracy in computer-based identification for histopathology data.

In [26], authors proposed a method which used multiple convolutional layers to gather gradient information in different combination of structural information. They proposed a method that can efficiently handles classifications of big data from different sources. They differentiate this method with different conventional classification techniques. This proposed method can be used in intelligent medical treatment and clinical practices, which based on mobile terminal.

In [27], an algorithm is presented to enhance the performance of X-Ray classification. Existing classification methods represent the image using only common image features derived from pre-defined features, which restricts the ability of image classification. Proposed algorithm consists of late fusion of domain transferred convolutional neural networks (DT-CNNs) with sparse spatial pyramid (SSP) features. This technique is implemented on public data set of X-Ray images and differentiate with existing approaches. Experimental results show that proposed model is perfect for classification.

In [28], author have used deep ResNets with different depth and width for spectral spatial classification. Two public ally available data sets are used for classification. When their depth increases classification performance of deep learning models reduce its performance. Therefore, to increase the performance author used two different models on different databases. To check the efficiency of proposed technique author applied this technique on various model settings. The hypothetical results show that the proposed technique shows the promising classification performance and improve the accuracy of classifications of CNNs.

In [29], a new method is presented for POLSAR image classification that consists of three steps, firstly, polarimetric information is used to get the edge power calculation and algorithm of watershed is used on this calculation. In second step, a table is made to find the most acceptable regions to integrate. Finally, region-based affinity propagation clustering is engaged for getting the earliest results and these initial results are used to acquire the final classification results. Author used two different data sets to check the effectiveness of this model and compare them with excising models. The proposed model results show that our proposed model can better differentiate the edge between different classes compared to other two methods.

In this paper [30], author evaluates three important factors on data set characteristics, transfer learning and deep CNN architecture. Through these factors evaluate the performance of proposed model.

In [31], for the interaction of human with virtual objects remote controls or depth sensors are used which are impossible to use in outdoor environment. For such devices to be controlled with human hands in outdoor environment, author proposed Faster R-CNN for hand detection and pose classification. For training and testing of Faster R-CNN, author

collected a hand pose data set with 111,362 images. Results of proposed model shows the mean average precision of 95%.

In [32], author concentrate on removing the feature redundancy of the images and to improve the classification accuracy. For this purpose, an algorithm SPM-PCA is proposed, which integrates the Spatial Pyramid Matching (SPM) and PCA for better image classification. This proposed model can enhance efficiency and classification performance through conditionality limitation.

In [33], to solve the problem of low accuracy of military scene image recognition author proposed a scene recognition method based on CNN and semantic information. Firstly, the military scene images are classified by CNN and then this result is enhanced by using semantic information. This proposed method is then validated by collected image scene recognition data set. Observed results show that the accuracy of proposed model is greater than traditional CNN methods.

In [34], author presents a CNN based model, in which features of images are taken as region wise and performed classification on them to overcome the encoder time. These results are use in the encoder downstream systems for detect-ing the optimum coding unit in each of the block. For training CNN, author randomly selected 20k images from PASCAL data set and to analyze the performance of proposed algorithm author compared this model output with three other models output. The hypothetical results show that proposed model minimize the encoder time effectively.

In [35], for detecting abnormal problem on chest x-ray images a model called multi-CNNs is used which is based on convolutional neural network. Accurately diagnose of any disease is difficult task. Image diagnosis is crucial part, which allows doctors to detect earlier and correctly. Multiple convolutional neural networks are used in this model to determine input values, which also called multi-CNNs. Data set taken from a Binh hospital. Author also proposed a model called multi-CNN to integrate the different results of the model, which are called fusion rule. The hypothetical results show the feasibility of proposed model.

In this paper, a novel multi-scale super pixel-based fusion classification approach is proposed for hyper spectral images. The proposed scheme consists of three steps, in first step, the original hyper spectral image is uniformly distributed homogeneously into multi scale super pixels to perform from coarse to fine scales. Secondly, multi scale features are extracted and these features are used for classification at each scale. Finally, for multiple classifications a decision fusion is proposed. Experiments performed to check the accuracy of proposed technique and it shows 92.6% accuracy, which is better than the existing technique. [36].

Super pixel-based multiple local convolution neural network (SML-CNN) is proposed in [37]. It is proposed for MS images and panchromatic images. For super pixel, author extended thru clustering algorithm for segmentation of MS images and generating super pixel. To improve the classification accuracy, author combined the semantic information and detailed information. Experiments are conducted to show the effectiveness of proposed technique.

In [38], author proposed a framework for hyper-spectral image classification based on spatial spectral interest point to resolve the classification problem for large amount of data. Experiments are done to check the accuracy of proposed framework and results of experiments show that proposed classification algorithm is more effective than the existing classification algorithms.

In [39], an evolutionary classification method is proposed which is used to discover a relevant cell set. This technique uses Location-dependent image classification (LDIC), which is integrated by genetic algorithm (GA) integrated with case-based reasoning (CB). LDIC introduces a new image segmentation framework and describe the multiple classifiers and trained these classifiers. CBGA-LDIC decomposes the whole image into cells, make sets of these cells and then train the classifiers on these cells. The accuracy of this method is examined by some experiments and results show that this method produces good outcomes when acceptable integration of cells is selected.

In [40], authors used POLSAR for image classification. Firstly, a special linear transformation is used to obtain fast implementation Wishart distance. Then, a single hidden layer

NN is used for image classification using results obtained from the first step. Finally, multi-layer NN is used to obtain improved image classification. The simulation results showed

Techniques	Features	Data set	Limitations
CNN with nine layers [9]	Enhance classification Performance	Three data sets	Performance issues
Cross domain CNN [10]	Enhance classification performance	Multiple data sets	data set scarcity issue
Deep CNN technique, SVM [11]	Scene classification	21 classes land use data set	Temporal complexity
WAE, K-mean [12]	Improve the classification result	EPEX-Belgium	Over fitting problem
FS [13]	Classification process	PJM	Time Complexity
PCA [14]	Classification accuracy	AEMO	Over fitting
ISVM[15]	Classification accuracy	PJM	S
SAR [16]	Classification	s	Unnecessary Complexity
LiDAR [17]	Feature fusion		Hard to tune parameters
DT [18]	Classification of images	Tested on 400 images	Accuracy error
Curriculum learning method [19] CNN [20]	Improve the quality of semi-supervised classification image classification between abnormal and normal images	8 different data sets Singapore eye research institute (SERI)	semi-supervised classification problem Time Complexity
Spatially constrained (BOV) [21]	Image classification		Occurrence of visual words for each patch
patch-based approach [22]	Classification scene	Pecan Street Inc.	Expensive
CADe algorithm [23], [24]	detection of lungs abnormalities	IRISH Ireland	Time complexity
Quaternion representation for color images [25]	Problem of handcrafted features		inter-relationships between color information and intensity
multiple convolutional layers [26]	Extract gradient information	s	complexity
DT-CNNs [27]	Classification process	public data set of X-Ray images	complexity
Deep ResNets [28]	Spectral spatial classification	two commonly used data sets	Degrade performance
watershed algorithm[29]	Image classification	two different data sets	Effectiveness error
CNN architecture[30]	Classification	s	Performance issues
R-CNN[31]	Hand detection and pose classification	Hand pose data set with 111,362 images	S
SPM-PCA[32]	Classification accuracy	two different data sets	Dimensionality reduction
Scene recognition method based on CNN [33]	Image recognition	two different data sets	Low accuracy
Multi-CNNs[34]	Detecting abnormal problem	Binh hospital	Feasibility of our model.
Multi-scale super pixel-based fusion classification approach[35]	Hyper spectral images	s	Uniformly distribution
SML-CNN[36]	MS images	data sets	classification accuracy
Framework for hyperspectral image [37]	Image classification	545 images	large amount of data
LDIC, GA[38]	image segmentation	Data from lab	Effectiveness error
POLSAR[39]	Image classification	768000 images	Spatial information was not considered
GSC[40]	classification accuracy	Three different data sets	supervised information was not take into consideration
IRPDL[41]	Image classification	Breast MRI	Effectiveness error
tomatoes[42]	Color shape and texture classification	Data taken from factory	Disease classification
Novel method[43]	Classify the melanocytic tumors	Two different derooscopy databases	lesion objects
Cube CNN-SVM[44]	Target pixel and spectral in-formation of the neighbor's classification	Kennedy Space Centre (KSC), Pavia University Scene (PU) and Indian Pines	CCS method for KSC dataset.

that 768000 images could be classified in 0.53 seconds. Spatial information was not considered in detail in this paper.

In [41], authors proposed an approach based on the use of possibility reasoning concepts, which exploits expert knowledge sources and ground seeds learning. The proposed approach is termed as Iterative Refinement of Possibility Distributions by Learning (IRPDL). The performance is compared with three existing methods. The proposed technique outperforms the existing techniques. The computational complexity is reduced. Breast MRI data set is used for image classification.

In [42], spectral and spatial information is integrate into Group Sparse Coding (GSC) via clusters. Each cluster is an adaptive spatial partition of pixels. In this paper, three different data sets are being used for experimental evaluation. In this literature, kernel is also incorporate into GSC to deal with the non-linear relationships. The proposed methods improved classification accuracy and provides distinct classification maps at granular level. The drawback was that the supervised information was not take into consideration. In [43], tomatoes are classified in five different types of disease groups. The classification was done on basis of color, shape and texture features. The classification done among healthy and unhealthy tomatoes. The disease classification done into six different classes. The overall classification achieved 97.3% accuracy.

In [44], authors proposed a novel method to classify the melanocytic tumors. The proposed algorithm has three steps: extraction of lesions, extraction of tumors features characteristics and finally the classification of lesion objects using an ensemble method. Experiments are performed on two different dermoscopy databases. Images of xanthous and Caucasian races included in this data sets. The experimental outcome showed that the classification accuracy is enhance. In paper [45], a hybrid model of CNN and SVM, termed as Cube CNN-SVM (CCS) is proposed. It is used for the hyper spectral classification of images. In such type of classification, a target pixel and spectral information of the adjacent is arranged and used. Three different data sets are being use for classification: Kennedy Space Center (KSC), Pavia University Scene (PU) and Indian Pines. The experiments showed that classification accuracy is increase by 4% when using spatial strategy while it increased about 3% when using CCS method for KSC data set. Our contribution in this paper is: we surveyed different papers in which image classification techniques discussed. We compared all these techniques and concluded that CNN is best option for image classification.

III. CONVOLUTIONAL NEURAL NETWORK (CNN)

In this work, we define different techniques related to classification; however, CNN gives the better accuracy than the other techniques. CNN mainly consists in three layers: 1) goal of Convolutional layer is filtering and extract features from input 2) Pooling layer reduce the parameters when input size is too large 3) Activation layer, a value pass a function that squashes the value into a range. We use ReLu function commonly because it is cheap to perform.

CNN find the pattern of the image, Introductory few layers are used to discover lines and corners, this pattern then pass through CNN and start recognize more complex features as we get deeper. This property of CNN makes good at identifying objects in image. CNN gives better performance, improve classification accuracy and solve data scarcity issue also give better results in multiple data sets.

IV. OPEN ISSUES

There are some open issues of CNN:

1. Back propagation requires large data sets; therefore, it is not effective way of learning.
2. In images, there are neurons, which detects the values of image when it rotates or change the position. To some extent, data enhancement solves the problem but it does not get rid of it totally.

Images with single labeled category have different problems, when predict the accuracy different challenges linked with this task including scale variation, image deformation, illumination conditions, image occlusion etc. [46].

V. CONCLUSION

In this paper, we discussed different techniques for classification of images. Mostly input images are noisy and blurry which are not easily to classify. Accuracy estimation is also an essential part in image classification procedures. Finally, we compared different methods of classification and concluded that CNN is best option to classify images even if it contains noisy and blurry content and give better results in multiple data sets.

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