MATERIAL RECOGNITION USING CNN

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Abstract: Materials can be easily detected and identified by humans. The visual system of human is very fast and accurate and can perform complex tasks like material identification and detection very easily. In recent decades, computer vision systems have concentrated on the categorization and detection of a range of materials that seem to be prevalent in our circumstances, which has constituted a major sensory challenge. Learning the detection of objects in diverse photos, which requires a deep learning process, took use of latest developments in the field of Artificial Neural Networks, which enabled the capacity for training numerous neural network designs for extracting the features for this difficult job. Material classification is very important for applications in automatic visual surveillance system. The process of classifying material into predefined and semantically meaningful categories using its features is called material classification. In this paper, a new model is proposed for detection and classification of materials by taking the features to classify the detected materials using Deep Neural Network (DNN). Deep Neural Networks are capable of handling large higher dimensional data with billions of parameters as like human brain. Simulation results obtained illustrate that the proposed classifier model produces more accurate results for feature extraction and DNN for classification.

Keywords: Visual System, Artificial Neural Network, material classification, visual surveillance system, Deep Neural Network (DNN)

I. INTRODUCTION

Material recognition is the process of recognizing the constituent material of the object and it is a crucial step in many fields. Many approaches for material recognition have been developed over the last several years, but none have attained adequate efficiency. Predicting the typical look of different materials or significant features is the classic way for material identification. Several types of materials, on the other hand, would have a lot of surfaces and be aesthetically incredibly rich. And, depending on the illumination and environment, the visual feature would behave significantly. The difficulty in material recognition stems from the vast range of looks that each material might have, including plastic, which comes in a range of colours, textures, and reflectivity. There is a slew of additional elements that influence material identification, including reflection estimates, lighting, and perhaps other variables [1]. the fusion recognition

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problem is tackled by developing a dictionary learning model that can simultaneously learn the projection subspace and the latent common dictionary for the different measurements. In addition, an optimization algorithm is developed to effectively solve the common dictionary learning problem [2]. Pre-processing the acceleration signals is a crucial step in the present techniques. Until being input into the classifier, pure acceleration information is translated into Mel-frequency cepstral coefficients (MFCC) or Spectrogram. Despite the present approaches' good effectiveness, fine-tuning their pre-processing step by scratch is time-consuming [3]. Understanding to categorise things into classifications is a crucial ability for a diverse range of robot activities, as well as an ongoing research topic in robotics and computer vision.[4] Therefore, it is valuable to create a system that could achieve a material recognition automatically. Recognizing materials from colour images is still a challenging problem today. While deep neural networks provide very good results on object recognition and has been the topic of a huge number of papers in the last decade, their adaptation to material images still requires some works to reach equivalent accuracies. Nevertheless, recent studies achieve very good results in material recognition with deep learning and in this paper, we propose to review most of them by focusing on three aspects: material image datasets, influence of the context and ad hoc descriptors for material appearance. Every aspect is introduced by a systematic manner and results from representative works are cited. We also present our own studies in this area and point out some open challenges for future works.

II. LITERATURE SURVEY

In the visual realm, whereby classifiers can be trained on enormous picture datasets without requiring autonomous contact with materials, object category acquisition and identification has received a lot of attention. The quality of manually gathered and extracted progress data is often poor, and various experiments to automate building progress monitoring have been done in recent years. Automated progress monitoring has grown in popularity at a near-exponential rate in the recent decade, promising to improve the process' efficiency and precision. Laser scanning, photogrammetry, and videogrammetry have all been utilised to automate the procedure in prior research [5]. The ability to reliably identify and distinguish the kind of material is a critical step in these systems, necessitating the development of robust and reliable ways to do this task and minimise error propagation in a monitoring system. Object/material recognition should be used in advanced progress monitoring approaches to extract contextual information [6,7,8.9.10.11,13].

Er. Navjot Kaur, et al discussed detecting people in images is key for several important application domains in computer vision. This paper presented an in-depth experimental study on pedestrian classification; multiple feature classifier combinations were examined with respect to their performance and efficiency. In investigate global versus local, as exemplified by PCA coefficients. In terms of classifiers, consider the popular Support Vector Machines (SVMs), Adaptive boost with SVM. Experiments are performed on a large data set consisting of 4,000 pedestrian and more than statistically meaningful results are obtained by analysing performance variances caused by varying training and test sets.

Anushka explained about the accomplished and accurate object detection that has been an important topic in the progress of computer vision systems. With the arrival of deep learning techniques, the purity for object detection has increased drastically. The paper aims to inclusive state of the art technique for the object detection with the goal of obtain high accuracy with a real time performance. A major challenge in many of the object detection system is the docility on other computer vision techniques for helping the deep learning-based perspective, which leads to slow and minimal performance. In this paper, we used a completely deep learning-based approach to solve the problems of object detection in an end-to-end fashion using wireless sensor network.

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Leveraging acoustic and visual information, Gao et al. [14] suggested a deep learning approach for tactile comprehension. Individual visual and haptic prediction networks were learned initially, and activations from these networks were then utilised to build a multimodal network. They showed that incorporating evidence from both sources enhances results. We remark that more study is needed to apply current training approaches to object category identification, which is yet largely untapped. We describe an architecture that considers three forms of tactile senses at the same period: visual, tactile, and aural, and leverages a significant lot of unique exploratory behaviours.

The advancements in neural networks and deep learning are used for designing a system for material recognition and tested the system on FMD with accuracy of 79.25%. A local database is built using materials of classes same as that pf FMD were collected from local environment with the help of Raspberry Pi3 by mounting a camera and obtained 90.5% accuracy. In this system, VGG-16 architecture is used to extract the features [15]. The pre-trained model of the ImageNet dataset is used. This network gains features of lower layers that are obtained from the huge ImageNet database since in most of the image classification tasks these features are fixed. In this, lower layers are frozen and only higher layers are updated. Only the fully connected layer has 10 neurons since there are 10 classes. The accuracy got reduced when the test ratio gradually increased.

The CUReT database [16] has 61 material specimens, each of which has been photographed under 205 distinct illumination and framework that defines. The Flicker Material Database (FMD) [10] has ten groups, each with 100 photos, which is extremely selective in order to add to each category's rich visually variance. While FMD has been used to material recognition, it is insufficient for real tangible recognition. OpenSurfaces, a large-scale material database created by Bell et al. [17][18], comprises more than 20,000 real-world-labelled sceneries. More than 3 million patches are catalogued in the Materials in Context Database (MINC), which is divided into 23 material groups.

The rest of the paper is organised as follows. Section 3 gives details of the Proposed Methodology. The evaluation results for state-of-the-art CNN architectures employing three widely used materials databases of real-world images are presented. Section 5 presents the result and discussion. Finally, conclusions are given in Section 6.

III. PROPOSED METHODOLOGY

In Deep Learning, a Convolutional Neural Network (CNN) is a class of artificial neural network (ANN) most commonly applied to analyze visual imagery. CNNs are also known as Shift Variant or Space Invariant Artificial Neural Networks (SIANN)[19], based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation-equivariant responses known as feature maps. CNNs are regularized versions of multilayer perceptron's. Multilayer perceptron's usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks makes them prone to overfitting data. CNNs take a different approach towards regularization, they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Deep learning is a branch of machine learning which is completely based on artificial neural networks, as neural network is going to mimic the human brain so deep learning is also a kind of mimic of human brain. It's on hype nowadays because earlier we did not have that much processing power and a lot of data. A formal definition of deep learning[20] is- neurons Deep learning is a particular kind of machine learning that achieves

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great power and flexibility by learning to represent the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones.

Data Flow Diagram:

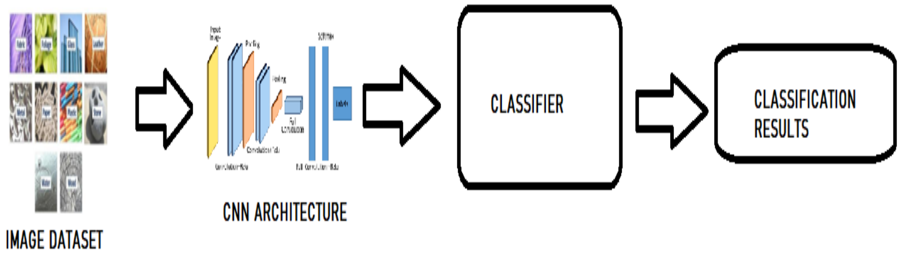

Fig 1 Data Flow

The work phase represented in fig 1 begins with the database being accessed, accompanied by the Convolutional Neural Network extracting features. The Convolutional Neural Network (CNN) is developed to easily identify and recognize the material type of the objects. The classification and recognition of variety of materials that are present in our surroundings become an important visual competition have been focused by computer vision systems in the recent years. Understanding the recognition of the materials in different images that involve a deep learning process made use of the recent development in the field of Artificial Neural Networks brought the ability to train various neural network architectures for the extraction of features for this challenging task. In this work, state-of-the-art Convolutional Neural Network (CNN) techniques are used to classify materials and also compare the results obtained by them. The results are gathered over two material data sets applying the two popular approaches of Transfer Learning. These characteristics are utilised to train the Neural Network to produce accurate outcomes for each category's materials. A total of 70% of the data set is used for training, while 30% is used for evaluation.

The CNNs system architecture illustrated in fig 2 consists of the training data images, database, image argumentation, predictive CNN model, feature extradition, feature selection, Django framework etc. The database consists of the images that is to be given to the system and the system is trained based on these images. At the time of training the system, the image is augmented by the system and the feature of the image is extracted via using the predictive CNN model [21]. Once the feature of the image is extracted, the required feature of the image is selected by the system. Now, the system will be completely trained. The trained datasets are now converted into H5 file and stored to avoid the wastage of time every time to recognize the material.

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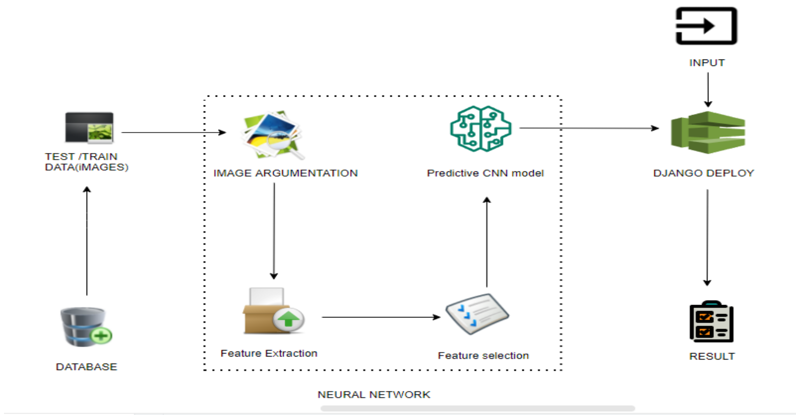

Fig 2 System Architecture

This H5 file will be deployed in the Django framework and the desired result can be obtained from there.

In Feature Extraction step, details such as Rows and Column are entered to the model, which does features extraction. GoogleNet, VGGNet-19 & Alexnet networks are used to perform the task, these networks were pre-trained on the huge data set known as ImageNet dataset used in image classification tasks. In FMD & Modified FMD datasets, data is divided into Training and Validation. Training dataset is 80% of the whole dataset and Validation is 20%. Pre-trained models on ImageNet have been used corresponding to the architectures used for training the images.

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. Their network consists of four layers with 1,024 input units, 256 units in the first hidden layer, eight units in the second hidden layer, and two output units. Input layer in CNN contain image data. Image data is represented by three dimensional matrixes. It needs to reshape it into a single column. Suppose you have image of dimension 28 x 28 =784, it need to convert it into 784 x 1 before feeding into input.

Convo layer[22] is sometimes called feature extractor layer because features of the image are get extracted within this layer. First of all, a part of image is connected to Convo layer to perform convolution operation as we saw earlier and calculating the dot product between receptive field and the filter. Result of the operation is single integer of the output volume. Then the filter over the next receptive field of the same input image by a Stride and do the same operation again. It will repeat the same process again and again until it goes through the whole image. The output will be the input for the next layer.

Pooling layer is used to reduce the spatial volume of input image after convolution. It is used between two convolution layers. If it applies FC after Convo layer without applying pooling or max pooling, then it will be computationally expensive. So, the max pooling is only way to

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reduce the spatial volume of input image. It has applied max pooling in single depth slice with Stride of 2. It can observe the 4 x 4-dimension input is reducing to 2 x 2 dimensions. Fully connected layer[17] involves weights, biases, and neurons. It connects neurons in one layer to neurons in another layer. It is used to classify images between different categories by training. Softmax or Logistic layer is the last layer of CNN. It resides at the end of FC layer. Logistic is used for binary classification and softmax is for multi- classification. Output layer contains the label which is in the form of one-hot encoded.

The two datasets are evaluated by all the three neural network models in the two approaches of Transfer Learning. Training is continued with increasing epochs until the loss function is decreased and results were obtained. Accuracy is computed to evaluate the performance. The confusion matrix and classification report are evaluated for the two approaches of all the three network models under two data sets. Also, the loss function and validation accuracy for validation data are determined. the trained deep learning model is converted into hierarchical data format file (.h5 file) which is then deployed in our django framework for providing better user interface and predicting the output whether the given material image is Fabric / Glass / Plastic / Stone / Wooden.

IV. RESULT & DISCUSSION

Our primary objective is comprehensive material classification, but we're also intrigued in seeing various CNN architectures categorise individual regions the best. AlexNet [13], VGG-16 [14], and GoogLeNet [16] were the highest yielding networks among the networks and parameter changes we tested. AlexNet and GoogLeNet are re-implementations of AlexNet and GoogLeNet, respectively. The manual performance calculation for CNN is illustrated in fig 3. The fig 4 represents the accuracy vs epoch.

```
Epoch 1/5
32/32 [==============================] - 15s 472ms/step - loss: 2.9672 - accuracy: 0.4374 - val_loss: 0.6885 - val_accuracy: 0.
7480
Epoch 2/5
32/32 [==============================] - 15s 482ms/step - loss: 0.8101 - accuracy: 0.6898 - val_loss: 0.6015 - val_accuracy: 0.
7676
Epoch 3/5
32/32 [==============================] - 14s 446ms/step - loss: 0.6356 - accuracy: 0.7622 - val_loss: 0.5129 - val_accuracy: 0.
8164
Epoch 4/5
32/32 [==============================] - 14s 424ms/step - loss: 0.5062 - accuracy: 0.8092 - val_loss: 0.3728 - val_accuracy: 0.
8750
Epoch 5/5
32/32 [==============================] - 14s 438ms/step - loss: 0.4327 - accuracy: 0.8434 - val_loss: 0.2711 - val_accuracy: 0.
9062
```

Fig 3: Manual CNN

AlexNet is the name of a convolutional neural network which has had a largeimpact on the field of machine learning, specifically in the application of deep learning to machine vision. AlexNet was the first convolutional network which used GPU to boost performance.

AlexNet architecture is illustrated in fig 5 that consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. Each convolutional layer consists of convolutional filters and a nonlinear activation function ReLU. The pooling layers are used to perform max pooling.

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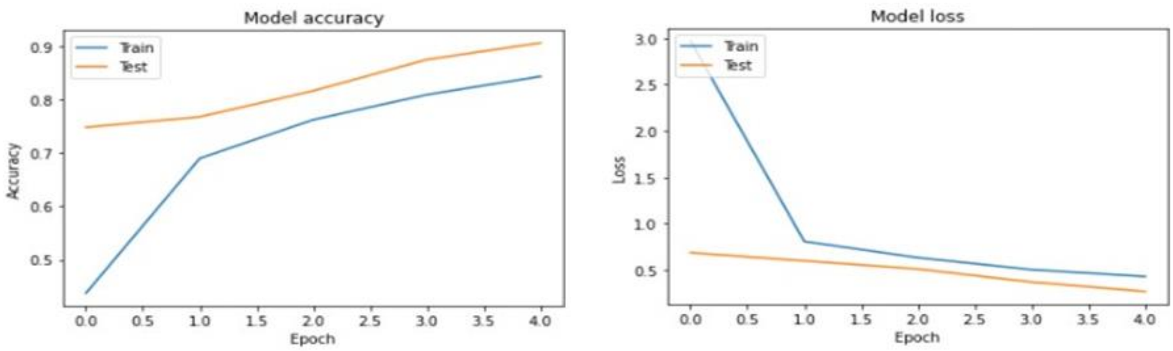

Fig 4: Accuracy and loss vs Epoch

Pooling layers are similar to convolutional layers, but they perform a specific function such as max pooling, which takes the maximum value in a certain filter region, or average pooling, which takes the average value in a filterregion. These are typically used to reduce the dimensionality of the network. Fully connected layers are placed before the classification output of a CNN and are used to flatten the results before classification. This is similar to the output layer of an MLP. The accuracies of these knowledge-based classifiers are shown in Fig. 6 and Fig.7.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 60, 60, 96)	34944
activation_7 (Activation)	(None, 60, 60, 96)	0
max_pooling2d_2 (MaxPooling2	(None, 30, 30, 96)	0
conv2d_4 (Conv2D)	(None, 20, 20, 256)	2973952
activation_8 (Activation)	(None, 20, 20, 256)	0
max_pooling2d_3 (MaxPooling2	(None, 10, 10, 256)	0
conv2d_5 (Conv2D)	(None, 8, 8, 384)	885120
activation_9 (Activation)	(None, 8, 8, 384)	0
flatten_1 (Flatten)	(None, 24576)	0
dense_4 (Dense)	(None, 4096)	100667392
activation_10 (Activation)	(None, 4096)	0
dropout_3 (Dropout)	(None, 4096)	0
dense_5 (Dense)	(None, 4096)	16781312
activation_11 (Activation)	(None, 4096)	0
dropout_4 (Dropout)	(None, 4096)	0
dense_6 (Dense)	(None, 1000)	4097000
activation_12 (Activation)	(None, 1000)	0
dropout_5 (Dropout)	(None, 1000)	0
dense_7 (Dense)	(None, 5)	5005
activation_13 (Activation)	(None, 5)	0

Total params: 125,444,725
Trainable params: 125,444,725
Non-trainable params: 0

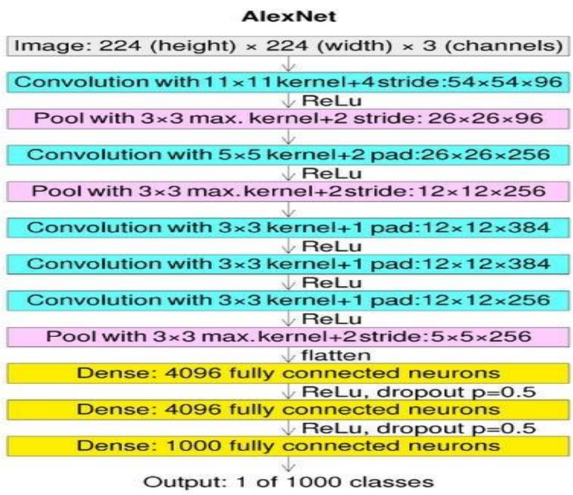

Fig 5: AlexNet Architecture

Fig 6: AlexNet Accuracy

Convolutional layers are the layers where filters are applied to the originalimage, or to other feature maps in a deep CNN[23,24,25,26,27]. This is where most of the user-specified parameters are in the network. The most important parameters are the number of kernels and the size of the kernels.

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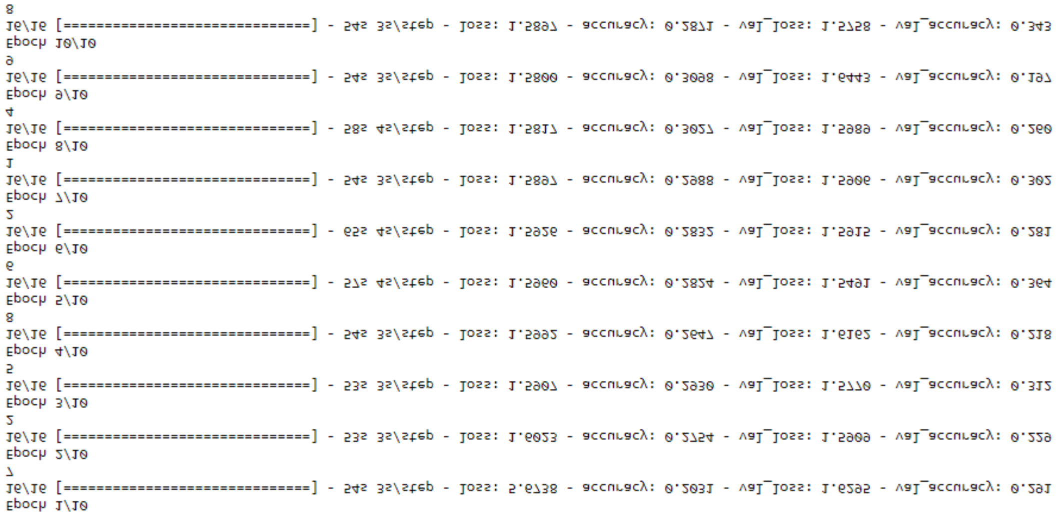
Fig



7: AlexNet Performance Measure

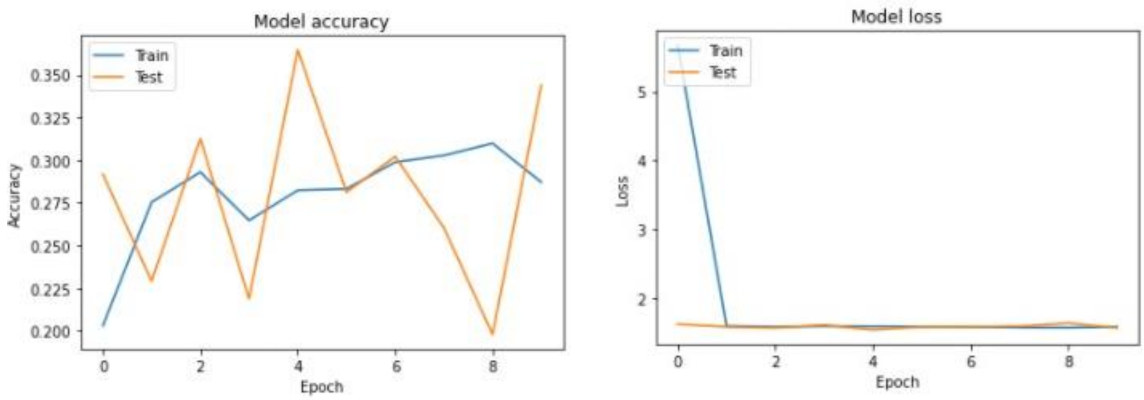


Fig 8: Epoch Vs Accuracy and Loss for AlexNEt

LeNet was one among the earliest convolutional neural networks which promoted the event of deep learning. After in numerous years of analysis and plenty of compelling iterations, the end result was named LeNet. LeNet-5 CNN architecture is made up of 7 layers which is represented in fig 10. The layer composition consists of 3 convolutional layers, 2 subsampling layers and 2 fully connected layers. The accuracies of classifiers are illustrated in Fig. 9.

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```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 83, 83, 32)        896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 41, 41, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 13, 13, 128)       36992
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 6, 6, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 4608)              0
_________________________________________________________________
dense (Dense)                (None, 256)               1179904
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 1285
=================================================================
Total params: 1,219,077
Trainable params: 1,219,077
Non-trainable params: 0
_________________________________________________________________
```

Fig 9: LeNet Accuracy

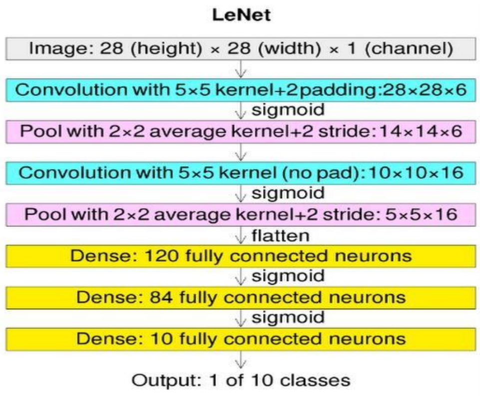

Fig 10: Architecture of LeNet

V. CONCLUSION

Material recognition has been a long-standing and difficult issue. We introduce MINC, a novel huge, open material library with a varied spectrum of materials from ordinary situations and deliberately planned interiors which is at likely an order of scale greater than previous databases. The contemporary deep learning methods are evaluated for simultaneous material classification and segmentation using this vast database, and acquire findings which outperform previous endeavors at material recognition. In this paper, research to classify materials over static different material images using deep learning techniques was developed. This paper focused on feature learning, which is one of DL promises. While feature engineering is not necessary, image pre-processing boosts classification accuracy. Hence, it reduces noise on the input data. Nowadays, material Classifications includes the use of feature engineering. The experimental results show that the CNN can achieve higher recognition accuracy than the knowledge-based classifiers, and our proposed Convolution based methods are superior to the prior methods.

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