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The Human Impact on Nutrition Education and Dietary Habits

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ABSTRACT

Deep neural networks have been developed in recent years to solve exceedingly complicated computer vision categorization challenges. Although the results obtained with these classifiers are frequently excellent, there are some industries that require better precision from these systems. Increasing Ensemble learning, which integrates several methods, can improve the accuracy of neural networks. Classifiers with the goal of picking a winner based on various characteristics about them These strategies have Despite the fact that they include distinct types of training models and can even produce over fitting with respect to the training data, hence datasets must be carefully selected the outcome. In this research, we are using the different transfer learning CNN algorithms applied on the grocery dataset. Once after considering the grocery dataset the preprocessing is performed and then the transfer learning algorithms are used for training the data and then the visualizations of confusion matrix along with accuracy and loss plots. Where we have used multiple transfer learning algorithms, we can select different models during the output checking.

Keywords: Deep learning, CNN, Transfer Learning, Grocery Dataset, Classification.

I. INTRODUCTION

The advancement of depth learning has greatly improved numerous fields, particularly speech processing and picture identification. Convolution neural networks have made significant strides in the handling of enormous data and distributed computing, making them significantly better to other conventional image recognition techniques. With an accuracy rate of over 99%, the depth convolution neural network constructed via supervised learning on behalf of the convolution neural network has been used to handwriting recognition. Additionally, face recognition has shown excellent outcomes. There are no reliable identification techniques or studies for identifying supermarket goods.

The data set pertaining to the supermarket goods has not been viewed, though. The difficulty of collecting data on supermarket items, which are many and identical, might be the explanation. We have used deep-level convolution neural network to extract the picture of the deep-level features to complete recognition, and we produced good

results. Traditional identification techniques extracting the characteristics of the shallow level are difficult to finish accurately.

The depth convolution neural network can recognize two-dimensional visuals with displacement, modest changing torsion, zoom, and lighting with some degree of stability. When employing the depth convolution neural network, the CNN eliminates the explicit extraction of the feature and implicitly learns from the training data since it derives the feature detection layer by learning the training data. Additionally, the network may achieve parallel learning since all of the neurons on the mapping plane have the same weight. When compared to conventional neurons that are connected to one another via neural networks, the deep convolution neural network has the following significant benefit.

The depth convolution neural network's network topology is unique and features local weight sharing. Speech recognition and image processing are two areas where it excels particularly. It more closely resembles a biological neural network in terms of neuron arrangement and learning organization. Particularly for multi-dimensional vector input pictures, the weight sharing properties greatly reduce network complexity. The depth convolution neural network's input picture may be obtained immediately, simplifying the feature extraction and classification procedure. Data reconstruction's complexity is avoided. Since practically all of the statistics for the feature are used in the usual approach of classifying images, we must first extract certain characteristics for identity determination. Explicit feature extraction is not simple, though, and the actual solutions to some application issues demonstrate that it is not always accurate. The depth convolution neural network learns implicitly from the training data rather than explicitly extracting the features. This reorganization of the network's structure and the reduction of the weight of network training result in a clear distinction between the depth convolution neural network and other neural network-based classifiers. The multi-layer perceptron incorporates a feature extraction mechanism that allows it to train on raw color and grayscale images, which can then be used to handle image-based classification problems.

In order to create a modest dataset for this study, we first finished collecting data on supermarket goods. The dataset is then trained using several transfer learning algorithms built on CNN, including VGG, Inception, and MobileNet. Finally, we utilised the models to classify the grocery data and compared the networks' recalls, precision, and accuracy.

II. Related works:

A hierarchical grocery store image dataset with visual and semantic labels: Visual assistance systems and other assistive technology must have image categorization models that can make precise predictions about their surroundings. We concentrate on the use of assistive technology in everyday tasks like cooking and shopping for persons who have visual impairments. The categorization of fruits, vegetables, and chilled goods, such as milk packets and juice cartons, in grocery shops is a difficult problem for this application, hence in this study, we offer a new benchmark dataset. This dataset not only includes a substantial amount of natural photos but also the relevant product information from an online retailer to allow the learning process to draw on various sources of structured knowledge. These details include an iconic picture of each type of item as well as the hierarchical organisation of the object classes. To train and test picture classification algorithms for assisting persons with vision impairments in outdoor settings, utilise this dataset. Along with benchmark findings, we also offer a multi-view variational auto encoder that can make use of the detailed product information in the dataset and pretrained convolutional neural networks, which are frequently used for picture interpretation.

An application of transfer learning and ensemble learning techniques for cervical histopathology image classification: Recent studies have concentrated on the use of Transfer Learning (TL) and Ensemble Learning (EL) techniques to the processing of cervical histopathology imaging data. However, there haven't been many studies that explain the stages of differentiation shown in the cervical histological images. Therefore, to distinguish between cervical histopathology images that are well, moderately, and badly differentiated, we present an Ensemble Transfer Learning (ETL) framework in this research. Inception-V3, Xception, VGG-16, and Resnet-50 have served as the foundation for our first set of TL structures. The classification performance is then enhanced by using a weighted voting-based EL method. After that, the recommended methodology is evaluated using a dataset of 307 images stained with three distinct immunohistochemical methods (AQP, HIF, and VEGF). In the experiment, we are able to distinguish poorly stained pictures of AQP and VEGF with an overall accuracy of 97.03% and 98.61%, respectively. The Herlev dataset is then used in a final experiment to distinguish between benign and malignant cells, and this one achieves an overall accuracy of 98.37%.

A fuzzy rankbased ensemble of CNN models for classification of cervical cytology: Cervical cancer affects more than 0.5 million women annually and kills more than 0.3 million of them. For a patient to be treated for the disease and have it removed from their body, early cancer identification is essential. Routine population-wide cancer screening is, however, constrained by the time-consuming and expensive cancer detection method that needs medical professionals to classify individual cells from a dyed slide containing more than 100,000 cervical cells. Computer-Aided Diagnosis (CAD) systems are therefore used as a practical choice for rapid and easy cancer detection. In this study, we develop such a method using three Convolutional Neural Network (CNN) architectures, namely Inception v3, Exception, and DenseNet-169, applied to the ImageNet dataset for Pap stained single pictures.

The recommended ensemble approach makes use of a fuzzy rank-based fusion of classifiers and two non-linear functions on the decision scores generated by the aforementioned base learners. The recommended ensemble strategy generates the final predictions on the test samples by taking into consideration the confidence in the predictions of the base classifiers, in contrast to the straightforward fusion procedures reported in the literature. The proposed model has been evaluated using a 5-fold cross-validation technique on two benchmark datasets that are available to the general public: the SIPaKMeD Pap Smear dataset and the Mendeley Liquid Based Cytology (LBC) dataset. On the SIPaKMeD Pap Smear dataset, the proposed framework performs with 98.55% classification accuracy and 98.52% sensitivity in its 2-class configuration and with 95.43% accuracy and 98.52% sensitivity in its 5-class configuration. On the Mendeley LBC dataset, accuracy and sensitivity are both 99.23%. The results obtained show the model's utility by outperforming many state-of-the-art models. Everyone has access to the relevant codes for this proposed model on GitHub.

High-dimensional dynamics of generalization error in neural networks: We investigate the usual dynamics of large gradient-descent-trained neural networks' generalisation. We concentrate on the "high-dimensional" regime, which is crucial for real-world applications, where the number of free parameters in the network is equal to or even higher than the number of instances in the dataset. Using random matrix theory and accurate solutions in linear models, we describe the generalization error and training error dynamics of learning and investigate how they depend on the dimensionality of data and signal to noise ratio of the learning problem. We find that the dynamics of gradient descent learning naturally prevent overtraining and overfitting in large networks. Overtraining is worse at intermediate network sizes when the effective number of free parameters equals the network size, therefore making a network smaller or larger helps reduce it. Additionally, starting with small initial weights is necessary for the high-dimensional domain's reduced generalization error. Then, we concentrate on non-linear neural networks and show that their capacity for generalization is unaffected by network scale. On the contrary, even without any form of early termination or regularization, it can actually decrease overtraining. We discover two distinct phenomena that underlie this behaviour in models that are too complete: First, there is a frozen subspace of the weights where gradient descent is ineffective, and second, the statistical properties of the high-dimensional regime lead to superior input condition correlations that avoid overtraining. We demonstrate that popular theories like Rademacher complexity are poor at predicting how effectively deep neural networks generalize, and we establish a substitute constraint that qualitatively matches the simulation-observed behaviour and accounts for the effects of frozen subspace and conditioning.

On splitting training and validation set: A comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning: Model validation is the most important phase in developing a supervised model. For the creation of a model with strong generalization performance, as well as for model validation, a reliable data splitting approach is required. In this study, we contrasted a variety of well-known data splitting methods. The MixSim model was used to generate nine simulated datasets with varying sample sizes and misclassification probabilities. These datasets were then submitted to discriminant analysis using partial least squares and support vector machines for classification. Data splitting methods included cross-validation, bootstrapping, bootstrapped Latin partition, the Kennard-Stone algorithm (K-S), and sample set partitioning based on joint X-Y distances (SPXY). These methods were used to separate the data into training and validation sets. The generalisation performances were calculated from the validation sets and compared to those found from the blind test sets, which were generated from the same distribution but concealed by the training/validation method used to create the model. The results showed that the generalisation performance characteristics estimated from the validation set rely on the amount of data. We found a significant difference between predicted performance from the validation set and that from the test set for all data splitting approaches applied to tiny datasets. This disparity decreased when more samples were made available for training and validation, since the models were then becoming closer to approximations of the central limit theory for the simulated datasets being used. We also found that the estimated model performance suffered from the training set's excess or deficiency of samples. This result indicates that a suitable balance between the sizes of the training set and validation set is required for a reliable assessment of model performance. Additionally, we found that estimations of the model's effectiveness using systematic sampling approaches like K-S and SPXY were frequently very inaccurate. This is most likely due to the fact that these methods are designed to collect the most representative samples first, which leaves a pretty large gap in the data.

III. Methodology

Proposed system:

In proposed method we are performing the cross validation for classification in grocery products identification using Convolution Neural Network (CNN) of deep learning along with the Transfer learning methods (MobileNet, Inception, VGG). As image analysis based approaches for grocery products classification. Hence, proper classification is important for the proper grocery products that which will be possible by using our proposed method. Block diagram of proposed method is shown below.

Inception algorithm:

This architecture has *22* layers in total! Using the dimension-reduced inception module, a neural network architecture is constructed. This is popularly known as **GoogLeNet (Inception v1)**. GoogLeNet has *9* such inception modules fitted linearly. It is *22* layers deep (*27*, including the pooling layers). At the end of the architecture, fully connected layers were replaced by a global average pooling which calculates the average of every feature map. This indeed dramatically declines the total number of parameters.

It uses a lot of tricks to push performance, both in terms of speed and accuracy. It is the winner of the ImageNet Large Scale Visual Recognition Competition in 2014, an image classification competition, which has a significant improvement over ZFNet (The winner in 2013), AlexNet (The winner in 2012) and has relatively lower error rate compared with the VGGNet (1st runner-up in 2014).

The major issues faced by deeper CNN models such as VGGNet were:

- Although, previous networks such as VGG achieved a remarkable accuracy on the ImageNet dataset, deploying these kinds of models is highly computationally expensive because of the deep architecture.

Very deep networks are susceptible to overfitting. It is also hard to pass gradient updates through the entire network.

MobileNet:

As the name applied, the MobileNet model is designed to be used in mobile applications, and it is Tensor Flow's first mobile computer vision model.

MobileNet uses **depthwise separable convolutions.** It significantly **reduces the number of parameters** when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks.

A depthwise separable convolution is made from two operations.

1. **Depthwise convolution.**
2. **Pointwise convolution**.

MobileNet is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast.

Depthwise convolution is the **channel-wise DK×DK spatial convolution**. Suppose in the figure above, and we have five channels; then, we will have 5 DK×DK spatial convolutions.

Pointwise convolution is the **1×1 convolution** to change the dimension

VGG:

The VGG network architecture was introduced by Simonyan and Zisserman in their 2014 paper, Very Deep Convolutional Networks for Large Scale Image Recognition.

This network is characterized by its simplicity, using only 3×3 convolutional layers stacked on top of each other in increasing depth. Reducing volume size is handled by max pooling. Two fully-connected layers, each with 4,096 nodes are then followed by a Softmax classifier. The "16" and "19" stand for the number of weight layers in the network. The VGG architecture is shown in below figure.

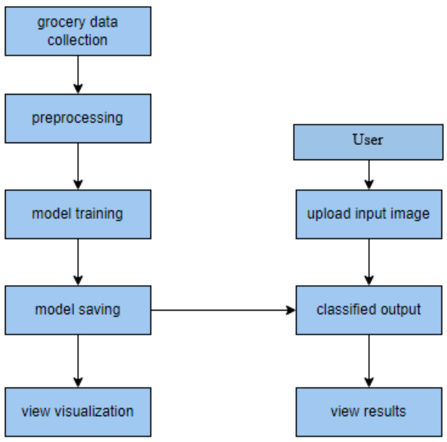


Figure 1: Block diagram

IV. Implementation:

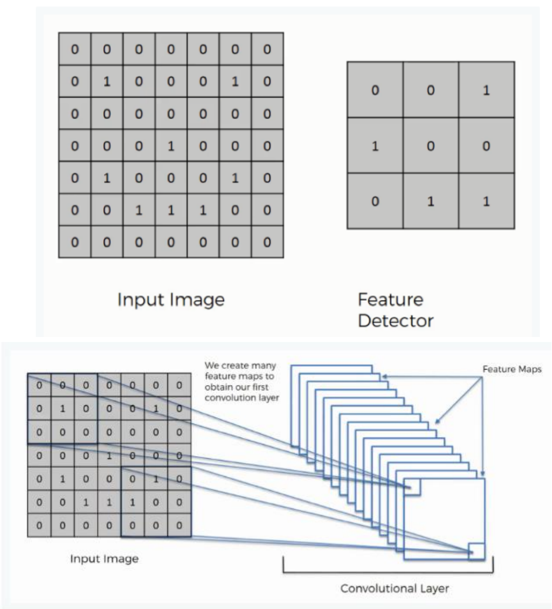
The project has implemented by using below listed algorithm.

1. Convolutional Neural Network

Step1: convolutional operation

The convolution operation is the first component of our strategy. We will discuss feature detectors in this phase since they essentially act as filters for neural networks. Additionally, we'll talk about feature maps, their parameters, how patterns are found, the detection layers, and how the results are laid out.

The Convolution Operation

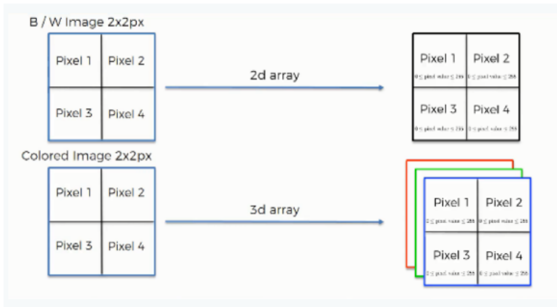


Step (1b): ReLU Layer

The Rectified Linear Unit or Relook will be used in the second portion of this process. We will discuss Relook layers and examine the role of linearity in Convolutional Neural Networks.

Although it's not required to comprehend CNN's, it wouldn't hurt to take a brief course to advance your knowledge.

Convolutional Neural Networks Scan Images



Step 2: Pooling Layer

We'll discuss pooling in this section and learn exactly how it typically operates. But max pooling will be the central concept in this situation. However, we'll discuss a variety of strategies, including mean (or total) pooling. This section will conclude with a demonstration created with a visual interactive tool that will undoubtedly clarify the entire idea for you.

Step 3: Flattening

Here's a quick explanation of the flattening procedure and how to switch between pooled and flattened layers when using convolutional neural networks.

Step 4: Full Connection

Everything we discussed in the previous section will be combined in this section. By understanding this, you'll be able to visualize Convolutional Neural Networks more clearly and understand how the "neurons" they create ultimately learn to classify pictures.

Summary

Finally, we'll put everything in perspective and provide a brief summary of the idea addressed in the section. If you think it will help you in any way (and it probably will), you should look at the additional tutorial that covers Cross-Entropy and Soft axe. Although it is not required for the course, it will benefit you greatly to be familiar with these principles since you will probably encounter them when working with convolutional neural networks.

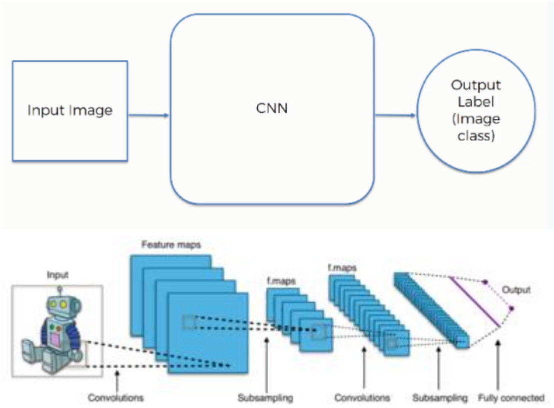
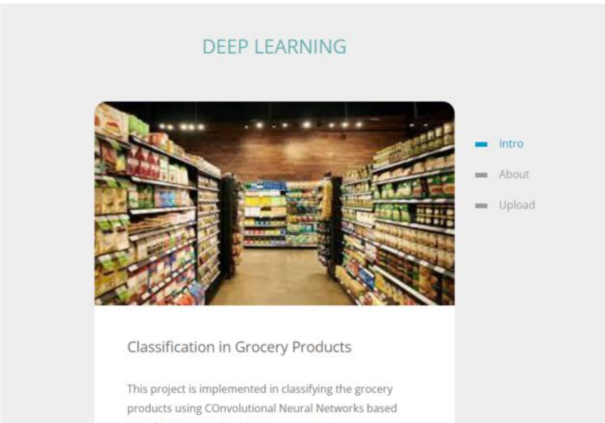


Fig. CNN Architecture

V. Results and Discussion:

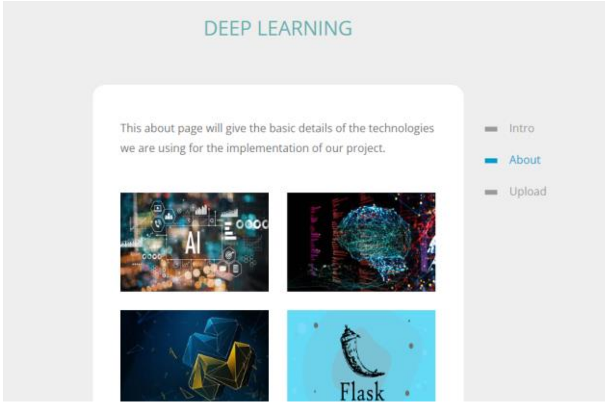
The following screenshots are depicted the flow and working process of project.

Home Page: This is the home page of classification in grocery products.



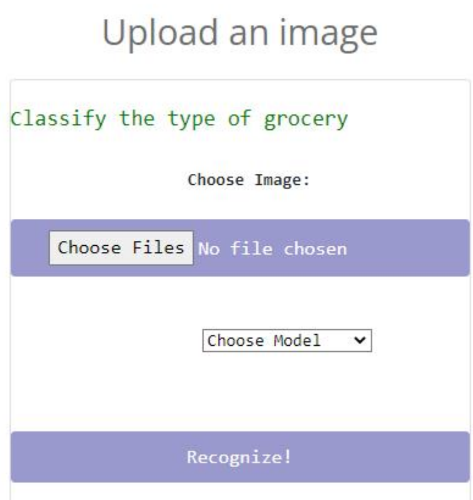
About our work:

Below is the about project page that which gives the details of our project of the technologies we have used.



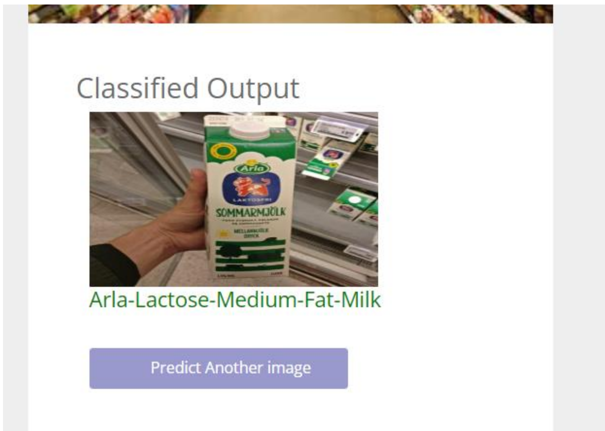
Upload Input Image:

Here we can upload the input image that which needs to be predicted.

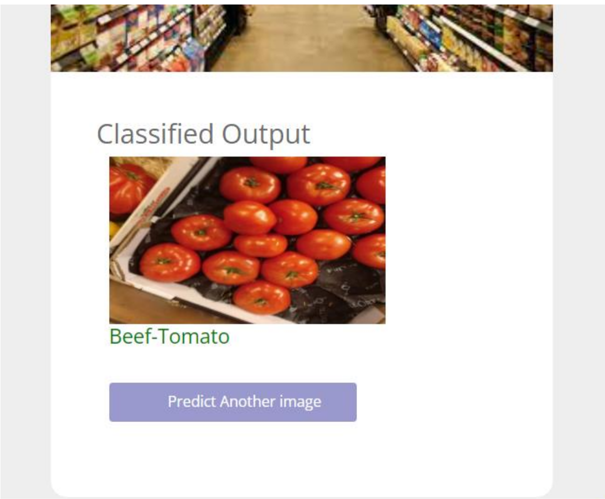


Predicted Output:

Below is the predicted output.



Predicted Output:
Below is the predicted output.



Quality Metrics:

Model	Accuracy	Precision	Recall	F1 Score
VGG	84.16	90.25	90.257	90.25
Inception	99.539	99.35	99.35	99.354
MobileNet	96.280	98.54	98.54	98.54

VI. Conclusion

In our proposed model we have worked on the grocery image dataset classification using the transfer learning algorithms, comparing the accuracy of the algorithms. We considered a dataset of grocery images, and trained using the CNN based transfer learning algorithm of deep learning. Once the training is completed, the input image is given from which the grocery is classified and the visualizations are viewed.

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