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Ensemble Deep Learning for Prediction of Palatable Mushrooms

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Abstract

Objective :
To develop a system that will classify the mushroom as edible or poisonous by processing the image acquired at the source during packaging at the business platform as well as at the consumer platform through an application installed in the imaging device.

Method :
Food is essential to meet the primary needs and to sustain human life. The calories and the nutrients in the food contribute to the wellbeing of the human being in terms of growth and function. Mushrooms are healthy food item that are rich in vitamins which instill health benefits that include healthy skin, relief from high cholesterol levels and prevent heart disease. It also contains essential minerals like iron, phosphor, copper, potassium and selenium. Consumers prefer food products that are highly nutritious. The packaged food industry is becoming highly prominent due to the changing life style, easy cooking and ready consumption. Applications are available to scan QR code and obtain data on ingredients, nutritional facts and expiry of a packaged product. The authenticity of the product can be improved with the intervention of the technology. Several machine learning methods exist to predict mushrooms as edible or poisonous based on various textual attributes namely the cap, stem and the color of the mushrooms. Currently deep learning is an emerging machine learning technique which could be applied for various classification and prediction with high accuracy through stacked neural networks. In this study, the mushroom images are captured using any imaging device and directly processed to classify them as palatable or not using deep learning network.

Findings :
Large mushroom image data set is used to train the classifier for binary classification as edible or poisonous. Image augmentation is used to generate multiple images to increase the training and validation mushroom image data sets. The primary focus is to minimize the False Positive Rate by choosing an appropriate model. To realize the ensemble model, optimizers namely rmsprop, adagrand and adamax are experimented along with convolution neural network having multiple hidden layers of dynamic parameters are used. The metrics considered for performance evaluation are Precision, Recall, F-Score and Likelihood ratio. The model accuracy resulted in the range of 80 to 85 percent on the test data.

Keywords:

DeepLearning;
ANN;
CNN;
Ensemble;
Binary Classification;
Mushroom Prediction.

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1. Introduction

The Technology has penetrated into every aspect of human life. It has brought in innovations in production and services industry. Food processing and packaging industry and healthcare services are the two sectors that are highly benefitted by technology. Though the consumer's convenience is one of the concerns, ensuring food safety must be the priority. The authenticity of the packaged food products though available in the labels, at times the way the products are stored may invite harmful bacteria to grow and cause food poisoning. Intervention of technology can solve this problem by automatic classification of the item as palatable or not by clicking an image and predicting the product. Machine Learning algorithms can be exploited to achieve this task.

Machine Learning Algorithms can be categorized based on:

- Learning method
- Functional Similarity

The different learning methods are:

i) Supervised Learning:The prediction is made using training data that has pre-set labels.
ii) Un-Supervised Learning: The input does not have labels and pre-defined result
iii) Semi-Supervised Learning: The model should learn from partially labeled data and make predictions.

Neural Network inspired algorithms are machine learning algorithms based on functional similarity. Deep Learning algorithms are neural network inspired methods that uses large data sets to predict the result in a semi-supervised learning environment.Ensemble methods are the composition of multiple independently trained models whose predictions are combined to make the overall prediction.

Mushroom is one of the favorite food item consumed by many all over the world. It is a great source of antioxidant with countless medicinal values and innumerous health benefits. To classify this vegetable as edible or poisonous, the existing techniques rely on extracting most indicative features such as the cap, color and stem features. In this work, the classification model is based on the images of the mushrooms by building multiple layers of neural network model and predicting the mushroom as palatable or not.

The paper is organized as follows:Section 2 presents the literature survey of the related topics. Section 3 presents the proposed ensemble model used for mushroom classification, Section 4discusses the experimental results on generated mushroom data set and Section 5 concludes with scope and challenges of the work.

2. Related Work

Mushrooms have attracted the food and the biopharmaceutical industry because of its medicinal value and the nutritional values[14,19]. The worldwide diversity of mushroom species is roughly accounted as 0.14 million. Of these, 14,000 are known and 7,000 are considered to have varying levels of edibility. More than 2,000 species are safe and 700 are documented to have considerable pharmacological properties[14, 13, 15, 16].A plethora of classification algorithms are available to group the mushrooms into two classes edible and poisonous which can be supervised, semi-supervised and unsupervised. The various approaches followed to classify mushrooms include:

- Multi-Layer Preceptor(MLP) model which is a modeling and forecasting tool that uses a neural network to model data. It uses a supervised learning technique, which requires data to contain targets for training the network[7].
- Comparative studies between MLP and Base Radical Network (BRF) for classifying mushrooms specify that MLP gives better results on larger datasets whereas BRF works properly with small dataset[9].
- Similarly a comparative research between categorical data clustering (CDC) and cluster ensemble (CE) for clustering mushroom data has proved that CE has a better accuracy with respect to clustering data[5].
- Robot vision system of the mushroom harvesting robot is used to check if there is damage in mushroom and classify them as healthy or unhealthy using a fast and non-destructive method, Support Vector Machine (SVM). This method has accuracy of 90% and above[10].
- K-modes clustering algorithm is used to classify agro-based dataset from the UCI repository were analyzed to identify different combinations of attributes that are significant in grouping the mushroom data as poisonous or edible [3].

The major issues with all the above approaches which used the data from UCI repository or Kaggle is the number of attribute values which ranges from 22 to 23 to be specified each time a mushroom need to be classified. Every time the attribute is specified and an error occurs in the entry can lead to wrong classification. Hence the error rate is high in all of the above methods.

The major advantage of using images for classification is that segmentation accuracies decrease with increasing segmentation scales and the negative impacts of under-segmentation errors become significantly large at large scales and [2] there are both advantages and limitations in using object-based classification, and their trade-off determines the overall effect of object-based classification, which is dependent on the segmentation scales.

Machine Learning systems can be used to solve problems and to duplicate a human expert's skill, by training them with dataset until the system has achieved good performance[4]. It is the science of getting computers to act without being explicitly programmed. It uses training data sets of real-world to infer models that are more accurate than human could devise on their own. In the past decade, machine learning has given us self-driving cars, practical speech recognition, effective web search, and a vastly improved understanding of the human genome. It is so pervasive today that everyone probably use it dozens of times a day without knowing it.

There are some most difficult tasks in artificial intelligence, far outstripping the capabilities of normal machine learning techniques. In these cases, computer scientists turn to neural networks which have subset of machine learning algorithms.What sets neural networks apart from other machine learning algorithms is that they make use of an architecture inspired by the neurons in the human brain. These networks turn out to be well-suited to modeling high-level abstractions across a wide array of disciplines and industries [17].Conventional machine-learning techniques were limited in their ability to process natural data in their raw form. It is required to design a feature extractor to transform the raw data into feature vector from which the learning subsystem, could detect or classify patterns [6].

Representation learning is a set of methods that allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification. Deep-learning methods are representation-learning methods with multiple levels of representation, obtained by composing simple but non-linear modules that each transforms the representation at one level into a representation at a higher and more abstract level. With the composition of enough such transformations, very complex functions can be learned. For classification tasks, higher layers of representation amplify aspects of the input that are important for discrimination and suppress irrelevant variations. An image, for example, comes in the form of an array of pixel values, and the learned features in the first layer of representation typically represent the presence or absence of edges at particular orientations and locations in the image.The second layer typically detects motifs by spotting particular arrangements of edges, regardless of small variations in the edge positions. The third layer may assemble motifs into larger combinations that correspond to parts of familiar objects, and subsequent layers would detect objects as combinations of these parts. The key aspect of deep learning is that these layers of features are not designed by human engineers: they are learned from data using a general-purpose learning procedure [8].

Within neural networks, deep learning is generally used to describe particularly complex networks with many more layers than normal. The advantage of these added layers is that the networks are able to develop much greater levels of abstraction, which is necessary for certain complex tasks, like image recognition and automatic translation [1]. In survey [8], Yanndescribe that deep learning is becoming a mainstream technology for speech recognition at industrial scale.

In a survey [11], Dandonpresents how ensemble learning be applied to various deep learning systems to achieve greater recognition accuracy. Linear stacking methods for ensemble learning with applications specifically to speech-class and long-linear stacking methods for ensemble learning with applications connected deep neural networks were studied.

Deep architectures help deep learning by trading a more complicated space for better performance, in some cases,even for less computation time [2].

Ensemble methods use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone. Ensemble methods, such as superlearners, can often outperform deep learning with much less work in algorithm design. Alan introduces Deep Incremental Boosting, a new technique derived from AdaBoost, specifically adapted to work with Deep Learning methods, that reduces the required training time and improves generalization [12].

3. Proposed work

The proposed process architecture for automatic classification of mushroom image as edible or poisonous is shown in figure 1.

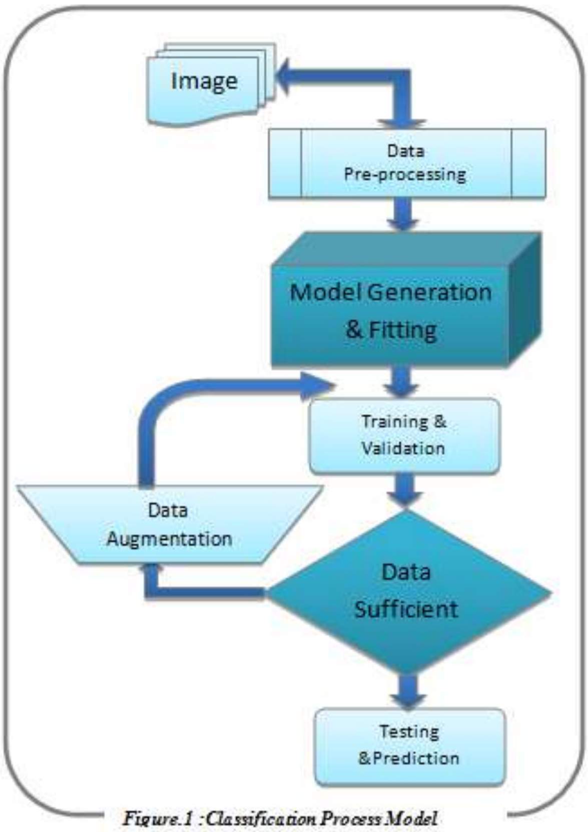

Figure.1 :Classification Process Model

3.1 Data Pre-processing

In this phase, each mushroom image in the mushroom image set is processed to have uniform image width and image height, the pixels of each plane of the RGB images are normalized and both class image sets are divided into r : v : t = training set : validation set : test data set. Since the classification is binary, the class categories are assigned as 0 for one class and 1 for another.

3.2 Model Generation and Model Fitting

To extract features and to address the curse of dimensionality problem, a stack of convolution layers with filters of size n and activation function ReLU (Rectified Linear Units) are generated for feature extraction and for subsampling, pooling layer of size m with a specific stride is generated as the bottom stack layers. On the top of stack fully connected layers are created to extract high level features and to converge at a single output as it is binary classification. The activation function used in this layer is generally sigmoid function. Model is compiled with appropriate optimizers and evaluation metrics.

3.3 Training and Validation

The neurons in the network learn the features of the data from the training data set through the model that was created in the previous phase. To achieve greater classification accuracy and to reduce the model loss and false positive rate, the training must be repeated by setting the number of epochs and batch size for processing. It can be observed that the accuracy of the model increases for each epoch.

3.4 Data Augmentation

No improvement in accuracy on the validation data set after few epochs reveal thatthe modelisoverfitting. One of the reasons for overfitting is insufficient training samples. Thus to increase the size of the training data set, unseen images can be generated through data augmentation. Images are augmented by random flips and shear transforms. If each image is augmented by l transformations then the training data set will increase by r * l. The network is aging re-trained and the accuracy graph is re-generated. This process improves the classification accuracy.

3.5 Testing and Prediction

Test image data sets consisting of both edible and poisonous mushrooms are subjected to the classifier to predict their class index. If the probability is less than 0.5, it is associated with class label 0 and if the probability is greater than 0.5, it is associated to class 1. The confusion matrix is computed for performance evaluation. The metrics namely, precision, recall, F_score are also measured.

4. Experimental Results

The mushroom images of JPG format with RGB color profile have been taken from various sources as dataset for this study. The dataset size is 380 images with the dimension of 100 x 100 (width x height) each. It has been randomly partitioned for training, validation and testing in the ratioof 60 : 30 : 10 percentage.

The proposed ensemble deep learning approach is implemented in Python Language with Tensorflow framework. Keras sequential model has been used to build the deep learning network. 2D Convolution layer is used to convolve with the layer input to produce outputs.

As Rectified Linear Unit (ReLU) activation function is the popular activation function for deep neural networks, it is used to define the output of internal layers. As the problem belongs to binary classification, sigmoid activation function is used in the output layer. A sample based discretization process called MaxPooling2D is used to reduce the dimensionality of the data and allowing for assumptions to be made about features contain

ed in sub-regions by binning. This is basically to help avoid over-fitting by providing an abstracted form of the representation. The default stride is used for convolution as well as pooling.

The model has been compiled with the objective loss function of binary_crossentropy. Different optimizers namely RMSprop, Adagrad, Adamaxand the metrics namely 'accuracy' and 'mean square error'are chosen to evaluate the performance of the model. Data augmentation has been applied to by increase the dataset andeliminate under-fitting.Operations such as shear, zoom, vertical flip and horizontal flip are performed on images. Different models have been generated by changing the filter size in the convolution layers, and optimizers at the higher level layers.

Table1 shows the values of various measures of the model before and after data augmentation and it is evident that the accuracy has increased after data augmentation. The impact of the three optimizers are compared through these measures and RMSprop is found to provide best accuracy in comparison to the optimizersAdagrad and Adamax. The results are shown in Table 2.

Table 1. Metrics of the model before and after augmentation

	Train			Validation		
	Accuracy	**Loss**	**MSE**	**Accuracy**	**Loss**	**MSE**
Before Augmentation	0.8622	0.3084	0.0992	0.8255	0.3619	0.1247
After Augmentation	0.8998	0.2777	0.0855	0.8462	0.3335	0.1118

Table 2. Comparison of optimizers

	Train			Validation		
	Accuracy	**Loss**	**MSE**	**Accuracy**	**Loss**	**MSE**
RMSprop	0.8998	0.2777	0.0855	0.8462	0.3335	0.1118
Adagrad	0.8702	0.209	0.1010	0.8301	0.3435	0.2196
Adamax	0.8693	0.3012	0.1029	0.8236	0.3578	0.2218

Table 3 presents the confusion matrix for the model with augmented data and RMSprop optimizer. Based on the results accuracy of the classifier through various measures are computed and is presented in Table 4. The results reveal that the composed model in this workis undoubtedly an efficient one in classifying the palatability of the mushroom. By observing the increase in the Precision and Recall measures and the decrease in the False Positive Rate (FPR) one can infer that the model is a significant. High FPR is a dangerous sign of the model as it will classify poisonous mushroom as an edible one.

Table 3. Confusion Matrix

		Predicted	
		Edible	**Poison**
Observed	**Edible**	True Positive 29	False Negative 5
	Poison	False Positive 4	True Negative 21

Table 4. Classification Metrics

Metric	Value
Precision	**0.8788**
Recall	**0.8530**
Accuracy	**0.8475**
False Positive Rate (Fall_Out)	**0.1600**
False Negative Rate (Miss Rate)	**0.1500**
F-Score	**0.8657**

The following figure 2, figure 3 and figure 4 represent all the model accuracy, model loss and errorand reveal that the generated ensemble is an efficient and effective in classifying the mushroom data.

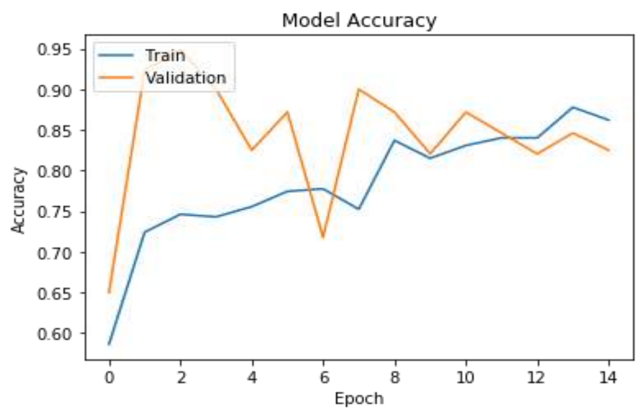

Figure2 : Model Accuracy

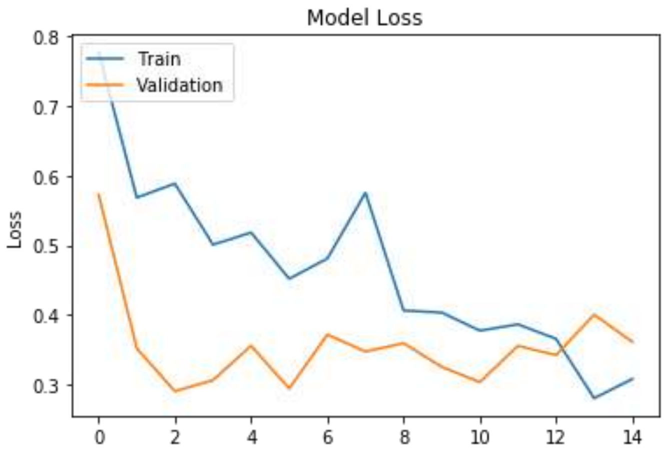

Figure3 : Model Loss

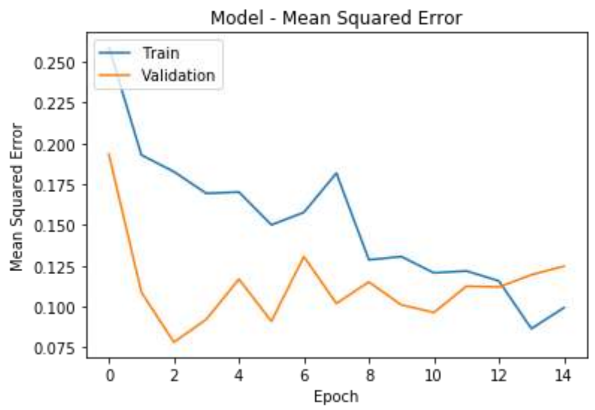

Figure4 : Model Error

5.Conclusion

The ensemble deep learning approach applied to classify the mushroom as edible or poisonous,based on all the experiments that have been carried out show that the composed model is an efficient one. The performance measures and the decrease in False Positive Rate (FPR) revealthat the procedure used for classification is significant with approximate efficiency of 85%.The efficiency of the model can be further increased by decreasing theFalse positive rate using the neural network ensemble.

The model created can be used by the food and packaging industry in order to automatically classify the mushrooms as edible or poisonous. A mobile application can be developed and customized to obtain all the details including nutritional values, edibility of a mushroom by just clickingthe image of the mushroom.

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