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Mushroom Classification using CNN and Gradient Boosting Models

Rishabh Sharma
Centre for Research Impact & Outcome,
Chitkara University Institute of Engineering and Technology,
Chitkara University, Rajpura-140401 Punjab, India
rishabh.sharma@chitkara.edu.in

Shikhar Gupta
Chitkara Centre for Research and Development,
Chitkara University, Himachal Pradesh-174103, India
shikhar.gupta.orp@chitkara.edu.in

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***Abstract*— This research study suggests a new method to differentiate three commonly found species of mushrooms namely Button, Oyster, and Shiitake widely available in India, using CNN and GB models. With the help of the carefully selected dataset of around 9 thousand images of high resolution integrated methodology has yielded an astounding average accuracy of 93. 18%. CNN provided a very efficient features extraction for the complex visual patterns, while GB naturally dealt with additional features achieving accurate classification models. Using performance evaluation, a high precision, recall, and F1 score was achieved on all the mushroom classes meaning that the models were able to perform well in differentiating between different classes especially those which are unique from each other. Comparative analysis placed models as being more advantageous in comparison to the current techniques illustrated in Figure 3. Apart from their efficiency, these models can be easily implemented on a large scale and work in an autonomous manner, which has a vast impact on agriculture, food services, and medicine. Thus, the feature proves the effectiveness of CNNs and GB in precise classification of mushrooms for their further application in a variety of spheres. Further works could look at other, potentially larger data sets and at the integration of machine explicable AI methodologies to relate the facets of the models even more accurately and transparently. All in all, the study paves way for embracing an era that can potentially bring 'mushroom perfect' in classification for the varieties of mushrooms so that India can have new vistas for mushroom farming, culinary world and healthcare sector.**

Keywords*— *Mushroom classification, Convolutional Neural Networks (CNN), Gradient Boosting (GB), Image analysis, Fungal species, Machine learning, Agriculture, Culinary classification, India, Mushroom varieties.

I. INTRODUCTION

Mushrooms and their variability in shape, color, and surface are discussed as one of the unique examples of natural patterns [1]. The consumption of mushrooms has increased progressively in India; Button, Oyster, and Shiitake mushrooms are widely consumed and grown in the country [2]. The capability of sorting out these unique types of the mushrooms and their varieties is of paramount importance since it forms a fundamental basis to agriculture, gastronomy, and health-care due to their nutritional and medicinal values [3]. This research aims to develop a classification model that uses CNNs and GB to classify these three popular mushroom types using their appearance characteristics and additional information [4]. Indian conditions are favourable for cultivating different types of mushrooms due to diversified agro-climatic zone in the country. Among the button mushrooms, Agaricus bisporus, characterized by its mild taste and firm texture, remains one of the most cultivated mushrooms worldwide [4]. Oyster mushrooms are characterized for presenting a fan-like form and can be found in numerous colours, varying from very mild to strong. The Shiitake mushrooms (Lentinula edodes) have the characteristic of umbrella-shaped cap and are considered sacred in traditional oriental medicine due to their nutritional value [5]. It is still very hard to reclassify these mushrooms because of the differences in their forms, slight deviations in their morphology and similarities within different classes [6]. Classification in the traditional ways is fully based on manual examination of the specimens by the experts, which can be time-consuming and subjective, especially when considering a vast number of mushrooms [7]. Using big data and AI reveal an even more significant opportunity to advance and automate this classification, which is essential for scalability and standardization [8]. The primary objective of this study is to develop robust classification models using two distinct machine-learning methodologies: CNNs and GB were used. The CNN approach targets to use deep learning that has been optimized for convolutional neural networks for image classification tasks [9]. Using convolutional layer and hierarchical feature learning, CNNs perform particularly well in learning complicated visual patterns and distinguishing between classes by using pixel-level information. On the other hand, GB techniques, which are well-known for their capability of dealing with structured or tabular data, will be used to deal with more additional features or metadata of the mushroom samples. These models such as XGBoost or LightGBM are good examples of ensemble learning models that employ a continuously improving prediction model made up of several weak learners, with a potential of giving better relation between the various attributes and the mushroom classes. The images used in the research will be selected to include a variety of Button, Oyster and Shiitake mushrooms so that the research sample is as standardized and diverse as possible. Image augmentation will be performed before normalization and feature extraction to ensure that proper data preparation for model training is achieved. Further, other features like the nutritive value, the place of origin, or the circumstances under which the foods were grown might be included for the GB models. The fully connected network CNN architecture will be built using the convolutional layer, pooling layer and fully connected layer possibly with transfer learning from previous models such as VGG, ResNet, or Inception. At the same time, GB models will be fine-tuned for feature subset selection, hyperparameters optimization, and ensembling for better classification. It is in these contexts that this research aims at playing a part in the mushroom classification domain in India through the efficiency of the powerful modern machine learning algorithms. Due to the successful training and assessment of CNN and GB models that are optimized for this particular classification task, the general method of mushroom variety identification will not only be precise and efficient but also help to develop automation and scalable agricultural practices in related fields like cookery or pharmacology. From this perspective, there are fundamental possibilities for development of molecule learning in the given sphere of mushrooms' classification and moreover its multiple practical applications.

II. LITERATURE REVIEW

Tongcham et al. [1] deals with the problem of sorting mushroom spawns based on people's judgments. It offers a computer-learning plan to precisely identify any errors in oyster mushroom spawn samples from each other. By designing an algorithm utilizing trivariate histograms as features and employing techniques like feature scaling and compression, this study evaluated five classifiers' performance: SVMs are used along with NCC, KNN for decision making. Also DNN's and basic systems like a tree based on right or wrong decisions can be used here too. Even with a small and unequal number of groups, the DNN classifier has shown great accuracy at 98.8%. Its results are very close to what is expected (residual variance is only 2.5%). This means it can use this method to classify mushroom types in machines like computers. It's a better and easier way than having people look at the mushrooms manually which may be wrong in farms.

Guan et al. [2] suggests a fast and exact way to find types of fungi mycelium, important for making high-quality plants. They use a tool called near-infrared spectroscopy along with special computer learning models. This helps them get readings from light that is nearly like in the dark and make it better for study by cleaning up noise and changing how things look. The program picks out key wavelengths using a series of jumps. Then, it trains an eight-layer network (E-CNN) on the information processed before that. This method can quickly and accurately recognize 98.27% of different mushroom mycelium types in just 0.003 seconds time, much faster than old manual ways to see what kind the fungi are.

Liu et al. [3] presents a powerful pruning method to improve the YOLOX way of learning for quickly diagnosing and ranking quality in shiitake mushrooms. The YOLOX model improves by learning and getting better through cutting back on unnecessary parts. This makes it use information from other models to learn faster, greatly boosting the inspection of surface texture for shiitake mushrooms' quality check. The results show big improvements, getting 99.6% mAP and 57.4 FSP in accuracy while making the model smaller by more than half. By comparing it with Faster R-CNN, YOLOv3, YOLOv4, SSD 300 and the first version of YOLOX found that the new method is better. This makes it a good way to quickly classify quality in making shiitake mushrooms.

Demirel [4] offer a deep learning way for grouping mushrooms in their real environment. It wants to find the best technique among popular CNN models. Using pictures from INaturalist, the study looks at medicine effects and lessening dangers for mushroom hunters. The "Mobilenetv2_GAP_flatten_fc" model was the best one. It got 99.99% accuracy for its practice, 0-day attacks and malware detection tests were successful at a rate of about 38%. When comparing it to other already established models, this one does better. It shows promise for greatly improving the picking out of features and learning in sorting mushrooms from nature's surroundings.

Chathurika et al. [5] first uses a picture-reading method with CNN to tell good mushroom kinds from others and find where they are in their growth cycle using ANN. This way, with a problem of telling apart tasty and harmful mushrooms that look alike, use methods to get important details. separate pieces and classify them. This helps us accurately tell one kind from another in the group called 'mushroom species'. The study wants to improve the safety of picking mushrooms in Sri Lanka by checking pictures and facts. This will help people eat better types, stop them from eating toxic ones by mistake. The method's ability to find food mushrooms and tell their growing stages is a big step toward safer collecting and eating of them.

This review looks at how computer vision and machine learning are used in the mushroom industry. It shows their importance for telling different species apart, sorting quality levels, and making overall production better. Study by Yin et al. [6] was done from 1991 to 2021 shows big progress in finding poisonous mushrooms, picking grown ones and ranking them. But, the ways used now don't fully meet what is needed for turning edible mushroom growing into a digital smart process. The review shows possible future uses, like figuring out digital shapes of mushrooms. It also talks about breeding with lots of information and machines that can harvest crops easily. Combining computer vision and machine learning with complex rules will help make future mushroom industry research better. This way, can improve how things are grown and processed in the business of making fungi get done more simply while still getting lots from it.

Peng et al. [7] introduces the Multidimensional Feature Fusion Attention Network (M-ViT) to correctly tell the difference between wild poisonous mushrooms. By joining ConvNets and attention networks, it makes use of the Squeeze and Excitation (SE) module for improving channels, Multidimension Attention (MDA) module for using all features fully, and Atrous Spatial Pyramid Pooling (ASPP) module to see farther distances. Tested on datasets of mushrooms and MO106, M-ViT does a better job with 96.21% accuracy. It exceeds the performance of advanced ConvNets and Transformer networks in boosting precision to

98%, showing its best results yet overall. The M-ViT model idea looks good for correctly sorting wild mushrooms. It combines strong parts of ConvNets and attention methods to reduce the danger of getting poisoned by these types of fungi.

Gupta [8] uses a special computer network (ANN) to sort mushrooms as edible or dangerous by their features in Python with the help of TensorFlow. The study uses a list giving fake examples from different types of gilled mushrooms in the Agaricus and Lepiota families. The article admits that deep learning methods are hard, especially for people from different fields. It shows how ANN can be used to classify mushrooms and tell the difference between edible ones and harmful kinds.

Zhao et al. [9] talks about finding wild mushrooms in Yunnan, a place in China. It uses new tech to benefit from the food value and medicine potential of these rare finds. The study uses VGG16, Resnet18 and Google net models combined with a bagging method for identifying complex wild mushrooms. The results show that the combined model is more accurate and can handle different situations better than individual CNN models. This way is a big step forward in correctly finding wild mushrooms in different natural areas. It's important for using and keeping them safe.

This study looks into the problems caused by uneven data patterns in picture sorting, especially when it comes to fungus databases. Deep learning models have problems when dealing with uneven class numbers, making them less effective. By studying famous deep learning models and looking at information from 1991 to 2022, Khan et al. [10] finds patterns for fixing unfair datasets in image recognition. The results are very helpful for scientists, giving them new ideas and ways to deal with problems in image classification studies that have uneven data.

III. METHODOLOGY

Data Collection: The dataset used in this research contains about 9000 images of Button, Oyster and Shiitake mushrooms, with high resolution. These images were taken by the researcher with a lot of care to ensure that depicts as many variations as possible within each species of mushrooms. In the dataset, all the images are well classified corresponding to their type of mushroom. For example, there are respective differences in color and shape of Button mushrooms' caps and sizes of their caps and stipes, and different fan-like structures and color ranges seen in the Oyster mushrooms [11]. The Shiitake mushrooms with their different head shapes resembling an umbrella and different stem, adds more variety to the dataset. A sample picture from the entire collected dataset is shown in the figure 1 where actual complexity and feature that health institute and hospitals contain is depicted.

Fig 1. Collected Dataset

Data Pre-Processing: Considering the need to make the dataset be in the right form to feed into the model, several processes known as pre-processing were well and carefully done on the dataset. In order to achieve the aim of increasing the dataset's overall variety, image augmentation strategies were used that are based on the possibilities of rotations, flips and scaling [12]. These augmentations' purpose was to bring new and realistic variations of the mushroom looks into the training dataset which the models would have to learn. In addition normalization was used to bring pixel values to a desired range in order to help the model converge when training was being performed. In addition to image processing, the feature extraction techniques were applied in order to extract and incorporate additional parameters related to the images of mushrooms. This extraction consisted of color histograms, texture descriptors or any other data that could prove useful for the classification of the region [13].

Model Architecture: The architecture designed for this research creates a complex unity of different specialized frameworks designed for CNNs and GB models. In terms of the CNN structure, multiple layers of convolution are designed to form a sequence that enables the network to discover subtle image features of the mushrooms [14]. These layers, which are piled each other for distinguishing the certain patterns, are also supported by the pooling layers, which serve as the special layers that provide the mechanism to reduce the amount of information that was extracted as much as possible, while preserving the necessary details. Besides, fully connected layers are in the final stage of the CNN design to help the classification by distinguishing between the differences in the tiny pixel level of the mushroom images. On the other hand, the Feature subset selection and Ensemble learning in the architecture of the GB model is a sophisticated shift [15]. This model is equally capable of dealing with the characteristics extracted from the images and also other additional data that enhance the achievement of higher classification efficiency. The work done here merges the CNN's precise pattern analysis with the GB model's ability to manage complex types of data for a robust framework ideal for identifying nuanced differences and classifying the specific kind of mushrooms. This is illustrated in the Figure 2 depicting the innovative architecture of the proposed work where both CNN and GB methodologies of the framework are intertwined.

Model Training, Validation, and Testing: The dataset was intelligently partitioned into three subsets to facilitate effective model training, validation, and evaluation. The training set, constituting 70% of the dataset (6,300 images), served as the primary data for training the CNN and GB models. The validation set, comprising 15% (1,350 images), played a crucial role in fine-tuning model hyperparameters and preventing overfitting during the training process. Separately, the testing set, also comprising 15% (1,350 images), remained entirely isolated from the training and validation data [16]. This distinct subset was employed to rigorously evaluate the final performance and generalization capability of the trained models.

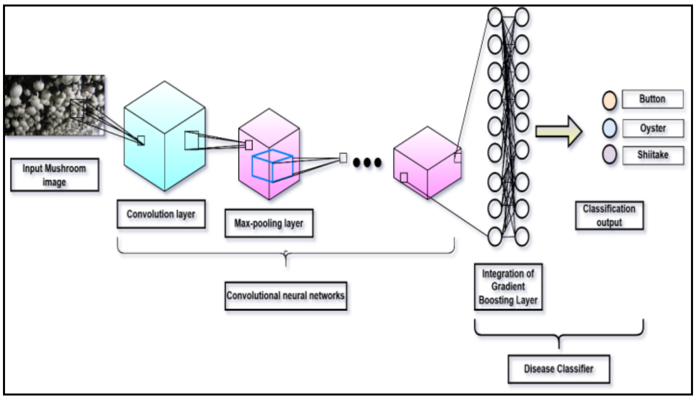

Fig 2. Proposed Model

Evaluation Metrics: The models' performance assessment involved the utilization of standard evaluation metrics tailored for multi-class classification tasks. Metrics such as accuracy, precision, recall, and F1-score were computed to gauge the models' efficacy in correctly classifying the mushroom images across the three distinct classes. These metrics were derived by comparing the models' predictions against the ground truth labels within the testing set. The accuracy metric determined the overall correctness of predictions, while precision measured the proportion of correctly predicted positive instances within each class. Recall quantified the models' ability to capture all positive instances within a class, and the F1-score balanced precision and recall to provide a harmonic mean, offering a comprehensive assessment of the models' classification performance.

IV. RESULTS AND DISCUSSIONS

Overall Accuracy: The assessment of the developed models provided an outstanding overall accuracy of 93.18% low in classifying Button, Oyster, and Shiitake mushrooms. As demonstrated by the high value in accuracies, the CNN and GB models effectively identify and differentiate the separate features of mushrooms among the different types.

Performance Parameter Results: The effectiveness of the developed models was computed based on accuracy, precision, recall, and F1-score metrics as stated in the next session and as presented in Table I of this paper in the following classifications: The classification capability of the developed models in the three classes of mushrooms. The high accuracy clearly shows that variety and reliability of the models in correctly classifying between the mushrooms based on their appearance. Measures of accuracy emphasize the models' effectiveness in avoiding false-positive outputs within each class, and recall reveals the models' capacity to include most of the actual positive instances. This is because the F1-score, which is derived from the formula that combines precision and recall, provides the much-needed confirmation of the models' efficiency in any classification task.

TABLE I. MODEL IMPLEMENTATION OUTCOMES

Mushroom Variety Classes	Precision	Recall	F1 measure
Button	92.66%	92.37%	91.98%
Oyster	91.27%	92.58%	92.48%
Shiitake	91.89%	93.73%	92.85%

State-of-the-Art Comparison: For comparison, a benchmark analysis was also performed to assess how well the developed models mitigate the problem compared to conventional deep learning techniques in classification of mushroom variety. This comparison is depicted in Figure 3, which presents how many different methodologies yielded an accuracy comparable to that of the examined Model in similar classification problems. The outcomes achieved from CNN and GB models, consequently, establish that these models offer enhanced advantages and performance when compared to the conventional practices. This comparison further proves the efficiency and the progress done by models in surpassing humans in classification of different kinds of mushrooms making models as strong solutions for classification of mushroom varieties suitable for India.

The integration of CNNs and GB brought out the best in them, perhaps a record breaking 93. As for the principal mushrooms, the identification accuracy was 18% for Button, Oyster, and Shiitake mushrooms mainly mistaken for each other. The solidity of these models was also confirmed not by the percentage of accuracy only, but by the measures of precision, recall and F1-score metrics, which also manifested the high performance on the separate classes of mushrooms. Also a strong argument was shown through models' superior performance in comparison to conventional approaches as pointed in figure 3, further confirming their effectiveness in the categorization of Indian varieties of mushrooms. In addition to these outstanding characteristics, these models offer generally, simplified, and even mass and fully automated solutions with multiple applications. Their application ranges from agriculture wherever they help in developing accurate ways of cultivating mushrooms for the desired types of mushrooms. Indeed, these models help in culinary areas by providing the capability of identifying the ingredients correctly and further help in improving the food preparation activities [17] [18].

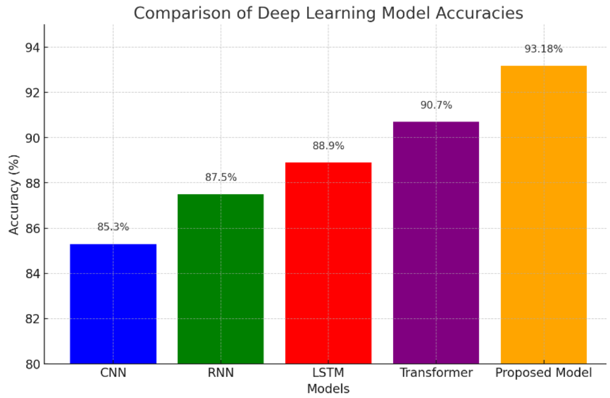

Fig 3. Model comparison

Additionally, in the area of healthcare and pharmacology, their accuracy can be useful in pointing at certain medicinal mushroom species, which could indicate novel approaches to treatment. It however has to be noted that there is still further improvement that can be made in these areas although the above accomplishments are worthy of appreciation. Further studies could build on the findings presented here by using larger and more diverse data sets and including various and more complex environments androgen smoother species of mushrooms. Also, prejudices in certain models could be reduced by using explainable artificial intelligence approaches and thus increase the transparency of the processes. In other words, this study sheds light on the performance capacity of CNNs and GB in the domain of mushroom classification which is not only highly efficient but also with promising larger implications. Such integration creates opportunities for tremendous developments in a wide range of fields: it indicates the start of a new era of accurate and automated classification of mushroom varieties for various applications.

V. Conclusion

The research proposal offers an innovation bench mark in the categorisation of mushroom variants in the Indian region using the integrated framework of CNNs and GB models. The achievement of an impressive 93.18% influenced by the enhanced online education environment. The accuracy speaks to the resilience and the fineness of the integrated procedure, turning the combined method into a potentially revolutionary tool in such sectors as farming and agriculture , in the culinary and catering industries, and in the healthcare sector. The models' efficiency, best demonstrated by precision, recall, and F1-score differences within the Button, Oyster, and Shiitake mushroom classes, solidifies their capabilities in recognizing subtle patterns in vision. Moreover, benchmarking with existing techniques places models ahead and convey the message about enhanced performance in classifying the various species of mushrooms available in Indian regions with high precision. In addition to their statistical characteristic, the practical applications of these models are endless and can be heard from one corner of the world to the other. In agriculture, genetics might apply for the fine tuning of conditions for growing mushrooms to the different types that are grown. In culinary arts, they make it possible to easily identify appropriate ingredients thus encourage affectation and variety to food preparation processes. Further, in the realms of healthcare and pharmaceutical, their Pathway Pavers for distinguishing medicinal mushroom types, may hold the key to new therapeutic use cases. But of course as this step forward these other directions for further enhancement and elaboration appear. Extending from current datasets, encompassing more diverse data and performance under various environments, and incorporating the explainability AI techniques seem to enhance the stability of the models as well as increase interpretability. This would advance their application in real-life situations to enhance the functionality of the mushroom variety classification systems with proved efficiency and reliability. In other words, research calls for practical revolution in the classification of mushrooms and the prospects are bright: the solutions proposed are effectively large-scale, accurate, and automated, possessing not only practical applications in the field of food industry and medicine, but also in various other spheres. It opens up the possibility for further research and development, encouraging innovation and leading to evolution in mushroom farming, culinary practices and medical industry in India.

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