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Visualization and classification of mushroom species with multi-feature fusion of metaheuristics-based convolutional neural network model

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HIGHLIGHTS

- The proposed model automatically detects mushroom species.
- Grad-CAM, LIME, and Heatmap methods based on CNN architectures are used to visualize mushroom images.
- The ASO algorithm has been successfully applied to residual block-based CNN models for feature selection.
- The hybrid model classification accuracy for different species of mushrooms is 95.45 %.

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ABSTRACT

Determining the correct mushroom species with the necessary ecological characteristics is critical to continue mushroom production, which is essential in gastronomy. The mushroom farmers and collectors technique may help identify toxic mushrooms by detecting poisonous mushrooms using images of different mushroom species with distinctive morphological features. However, it can be not easy to distinguish between species. This paper used a dataset of 6714 mushroom images obtained from nine different mushroom species to classify the mushroom species. For a more straightforward comprehension of mushroom images and feature extraction by reanalysis of data sets, data visualization was performed using Grad-CAM, LIME, and Heatmap methods. Residual block-based Convolutional Neural Network (CNN) architectures are trained to automatically classify the concatenated feature map obtained from the Grad-CAM, LIME, and Heatmap methods. After extracting the deep features of the images from each architecture, the Atom Search Optimization (ASO) algorithm has been used to select the most distinctive features. The 6714×9000 size of the concatenated feature map was reduced to 6714×600 using the ASO algorithm. Classification results were evaluated using six different classifiers based on the feature map obtained to determine the mushroom species. The nine classes of mushroom species were classified successfully with 95.45 % accuracy using the proposed model with the ASO algorithm and KNN classifier. The methodology introduces novel visualization techniques for interpreting CNN-based models' decisions in mushroom species classification tasks. Using metaheuristics-based CNN models with multi-feature fusion techniques allows the model to leverage diverse sources of information, potentially enhancing its ability to discriminate between mushroom species and achieve higher classification accuracy than existing methods. This study can advance the mushroom species classification field by introducing new methodologies, improving classification accuracy, providing insights into model interpretability, and facilitating knowledge transfer to related fields.

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1. Introduction

Mushrooms are called macrofungi and have extensive and unique fruit parts that can be seen with the naked eye and can be picked by hand [1]. Mushrooms, which can be consumed by humans and some living things as food, are divided into two separate groups as medicinal [2]. Mushroom species can be consumed as food products with high nutritional value. Mushrooms contain many minerals, such as potassium, iron, calcium, copper, vitamins B3 and B12, phosphorus, zinc, magnesium, selenium, and manganese. In addition, it is rich in Niacin, riboflavin, pantothenic, and conjugated linoleic acid [3]. The amount of protein it contains is as high as that in meat, milk, and eggs, and is one of the best sources of vitamin D [4,5]. It is also the only natural food source containing vitamin D besides animal sources. In this respect, mushrooms are considered the most critical food source for humans [6].

Around the world, an average of 150,000 species of mushrooms grow in the wild [7]. It has been determined that approximately 2500 of them are edible [8]. Edible wild mushroom species collected from nature are in greater demand than cultivated mushrooms. This increase in demand for wild mushrooms and their commercial potential has led to mushrooms gaining the feature of being a non-wood forest product [9]. Mushroom harvesting has become a source of livelihood for people because it does not require much labor, and the mushroom harvesting process is low-cost [10]. However, increased mushroom production demands and unconscious foraging recently have caused sustainability problems in mushroom cultivation [11]. Due to the high demand for mushrooms in developing countries, especially developed countries, the annual mushroom consumption per capita has increased to 3 kg [12].

Mushrooms can also be used as a supportive product in the prevention and treatment of many diseases because of the bioactive compounds they contain. It has been determined that most mushroom species collected from nature have medicinal benefits such as antitumor, antioxidant, antimicrobial, antiviral, and antiallergic [13]. The identification of mushrooms is an essential problem with a significant place in terms of living ecosystems and human life. However, visual identification of the mushrooms without contacting and harming them is critical regarding human health and the sustainability of mushroom resources. Despite this, the ability to identify mushroom species through mushroom images has not received sufficient attention from researchers, although it is a significant problem[14]. The main reason is that the data used in studies in this field are insufficient or imbalanced. Many types of mushrooms in nature have very subtle differences in their physical structures. For this reason, identifying mushroom species is an issue that even educated and experienced people have difficulty with. It is a valuable problem solution to use CNN. This deep learning method gives impressive results on vision problems and rapidly progresses daily in determining mushroom species. In our paper, classification was carried out using artificial intelligence and optimization methods to solve the problem of identifying mushroom species through their images. Thus, it can be helpful in matters such as carrying mushrooms to the future, protecting vital mushrooms, making sustainable management plans for mushroom resources, determining whether mushrooms are poisonous or not, botanical research, defining the class or subspecies of mushrooms, mushroom cultivation, processing processes of mushrooms and mushroom pickers.

This paper used a dataset with nine mushroom species to determine different samples. Data visualization was performed using Grad-CAM, LIME, and Heatmap methods for more straightforward interpretation and extraction of the salient features of mushroom species images. Residual block-based CNN architectures are preferred for feature extraction. The features obtained from the original mushroom species samples and these three methods have been concatenated into a single feature map. After a successful classification using residual block-based CNN models, the features obtained to improve the classification accuracy are determined using the ASO algorithm to increase classification efficiency. The new feature maps created by feature selection are classified using six different classifiers. The contributions of the proposed model to the literature are summarized as follows:

- It automatically detects mushroom species.
- A new open-access dataset consisting of 6714 mushroom images belonging to nine different mushroom species was used in training the proposed model.
- Grad-CAM, LIME, and Heatmap methods based on CNN architectures are used to visualize mushroom images. This combination was implemented for the first time in this paper to solve the mushroom species classification problem.
- The ASO algorithm has been successfully applied to residual block-based CNN models for feature selection.
- The hybrid model classification accuracy for different species of mushrooms is 95.45 %.
- Compared with similar research and pre-trained models, the proposed model produced more successful results.

The study may achieve higher classification accuracy by employing metaheuristics-based CNN models with multi-feature fusion than existing methods. This improvement could provide insights into the effectiveness of metaheuristics in optimizing CNN architectures for mushroom species classification. Using multi-feature fusion techniques allows the model to leverage diverse sources of information, potentially enhancing its ability to discriminate between mushroom species. This approach could shed light on the importance of integrating different features, such as morphological, textural, and spectral, for accurate species classification.

This paper introduces novel visualization techniques for interpreting CNN-based models' decisions in mushroom species classification tasks. These techniques could offer insights into the model's decision-making process, highlighting which features or regions of the input images are most influential in distinguishing between species. The proposed methodologies, such as metaheuristics-based optimization and multi-feature fusion, could broadly apply beyond mushroom species classification. Researchers in other fields may find inspiration in adapting these techniques to their image classification problems, advancing the state-of-the-art in computer vision and pattern recognition. By analyzing features extracted by the CNN model, the study may provide insights into the morphological characteristics most discriminative for distinguishing between mushroom species. This could contribute to understanding mushroom taxonomy and evolution and inform conservation efforts and ecological studies. Overall, the paper's scientific value lies in its potential to advance the field of mushroom species classification by introducing novel methodologies, improving classification accuracy, offering insights into model interpretability, and facilitating knowledge transfer to related domains.

The rest of this paper is as follows: the second section describes the data and methodologies employed. The third section explains the proposed model. The findings of the experimental research are presented in the fourth section. The discussion and conclusion sections follow, respectively.

2. Related works

One hot topic in the intersection of metaheuristics and CNNs is the development of novel optimization algorithms explicitly tailored to enhance the training efficiency and performance of CNNs [15]. Optimization is crucial in CNNs to feature selection or fine-tune the network's parameters, such as weights and biases, during training. This optimization aims to minimize the difference between the predicted output of the network and the actual output, thus improving the network's ability to classify and recognize patterns in data accurately. This section includes studies addressing the problem of mushroom species classification. There are not many studies in the literature that use metaheuristic algorithms to solve the mushroom classification problem.

In very few of these, deep learning approaches are supported with metaheuristic-based algorithms. This highlights the originality and innovative aspect of our work.

The Osprey Optimization Algorithm (OOA), which is used to increase the computational efficiency of Otsu's threshold binarization and get entire mushroom contour samples effectively, is one of the many steps in Wang et al.'s [16] comprehensive approach to solving the mushroom recognition problem. Then, a technique based on the upgraded VGG network (D-VGG) is presented for grading dried shiitake mushrooms. D-VGG has a high accuracy of 96.21 % in identifying mushrooms.

In a fungi identification competition held at CVPR 2018, 1400 species of mushrooms were classified from approximately 100,000 mushroom images. Various techniques, such as data augmentation over the state-of-the-art six CNN architectures and adjusting the predictions according to previous classes, have been used among the proposed approaches. Among these approaches, Inception-v4 achieved the highest performance at 52.6 % accuracy without training on ImageNet and data augmentation [17]. Peng et al. [18] developed an improved M-ViT deep learning-based wild mushroom classification system. They proposed an M-Vit model that combines the low-level features of wild mushrooms with high-level feature information. This study introduces M-Vit, a lightweight model that combines transformer and convolution, to the wild mushroom visual classification transformer model for the first time. With fewer model parameters, M-Vit improves the recognition rate. Because of the experiments, the mushroom dataset was predicted with 91.83 % accuracy using the proposed method.

Ottom et al. [19] tested various ML approaches to classify images of mushrooms into edible and toxic groups. They experimented with decision tree (DT), k-nearest neighbors (KNN), support vector machine (SVM) techniques, and essential feed-forward neural networks. In a further stage, they extracted features from the images to construct a feature matrix fed into the models above. With 94 % accuracy, the KNN technique outperformed the others in their testing when determining the actual size of the mushrooms. The accuracy decreased to 86 % if they relied solely on the visual characteristics extracted from the images. Kang et al. [20] evaluated the performance of three separate networks, AlexNet, VGGNet, and GoogLeNet, to classify 38 wild mushroom species over a dataset with 1478 sample images. The classification accuracy rate of the proposed method reached 82.63 %.

A smartphone application was created by Lidasan et al. [21] to determine whether or not mushrooms are toxic. The program uses probabilistic neural networks as a classifier and the GrabCut method for segmentation. Their program achieved a 92 % accuracy rate, with 133 mushroom images serving as training data. Yuan et al. [22] presented a technique based on the Inception-ResNet-v2 model for identifying wild mushrooms from a fine-grained image perspective. Nevertheless, this methodology does not account for the intricate background of the photos, resulting in comparatively low recognition accuracy. Ketwongsa et al. [23] proposed a scheme for differentiating between edible and toxic mushrooms. Three pre-trained models were contrasted in terms of testing duration and precision. By including the GoogleNet inception module layer and eliminating the fourth and fifth convolution layers from the original AlexNet model, the proposed model was created to transfer learning and enhance AlexNet. The training and testing times needed for the suggested model were found to be shorter while maintaining a high degree of accuracy. The proposed model showed accuracy scores of 95.50 % in R-CNN-based mushroom classification studies.

In this study, unlike existing studies, a hybrid method was developed to automatically classify the combined feature map obtained from Grad-CAM, LIME, and Heatmap methods in detecting the mushroom species and to justify the need to create residual block-based CNN architectures. By combining Grad-CAM, LIME, and Heatmap methods, the proposed method provides a comprehensive approach to visualizing and interpreting the decision-making process of a CNN model [24]. This enhanced interpretability is crucial for understanding why the model makes specific predictions, which can be valuable for researchers and practitioners in fields such as medicine, autonomous systems, and image analysis. Each visualization method captures different aspects of the model's attention and decision boundaries. By combining these methods, the proposed approach leverages the complementary information from each visualization technique, leading to a more comprehensive and nuanced understanding of the model's behavior [25]. The method automates the classification process by extracting features from the combined feature map and feeding them into a classification algorithm. This automation reduces the need for manual inspection and interpretation of visualization results, thereby streamlining the analysis pipeline and making it more scalable to large datasets and real-world applications[26]. The proposed method improves model performance by providing additional discriminative features or highlighting areas of uncertainty. This improvement could lead to more accurate and reliable predictions, especially in challenging classification tasks or domains with limited labeled data.

Residual block-based CNN architectures, such as ResNet, are highly effective in learning complex features from input data. Residual connections enable deeper networks to be trained more effectively by alleviating the vanishing gradient problem, thereby allowing the model to learn richer representations of input features [27]. The skip connections in residual blocks facilitate better gradient flow during backpropagation, which helps prevent degradation in model performance as the network depth increases. This property is particularly advantageous for training deep neural networks, enabling more stable and efficient optimization [28]. Their effectiveness in capturing hierarchical features and modeling complex relationships within data makes them a natural choice for many classification tasks, including those involving mushroom species.

Generally, the combination of Grad-CAM, LIME, and Heatmap methods for visualization and the use of Residual block-based CNN architectures for feature learning and classification represent innovative approaches that offer both interpretability and performance benefits for deep learning applications, including mushroom species classification.

3. Materials and methods

When the dataset sample images of mushroom species were examined, data visualization stages were applied to make it easier for food controllers and agricultural engineers to identify species and to reveal distinct features in obtaining accurate classification results. In this regard, the ASO algorithm used for feature selection and the hybrid model developed for mushroom species classification is mentioned, along with the dataset and visualization methods used in the paper. The flow diagram of the proposed method is illustrated in Fig. 1.

3.1. Mushroom dataset and image visualization

No method automatically detects all mushroom species growing in nature. Various studies have identified fungal species by classifying specific species using multiple methods. However, none of these studies provide sufficient detection of autonomous fungal species. A dataset of samples of nine different mushroom species, Entoloma, Boletus, Cortinarius, Hygrocybe, Amanita, Lactarius, Russula, Agaricus, and Suillus, was used. The mushroom dataset used In this paper was downloaded from the publicly shared Kaggle platform [29]. The number of samples for each class in the dataset is as follows: Amanita 750, Boletus 1073, Entoloma 364, Cortinarius 836, Hygrocybe 316, Russula 1148, Agaricus 353, Lactarius 1563, and Suillus 311. The mushroom species dataset contains 6714 sample images for nine classes. Fig. 2 provides image samples for each class in the mushroom dataset.

Visualizing images is used to analyze and comprehend data more effectively. There are various ways to execute this technique. In addition, it is widely applied in fields including data analysis, signal processing, picture visualization, and model development. This procedure makes better comprehension of the data and more effective decision-

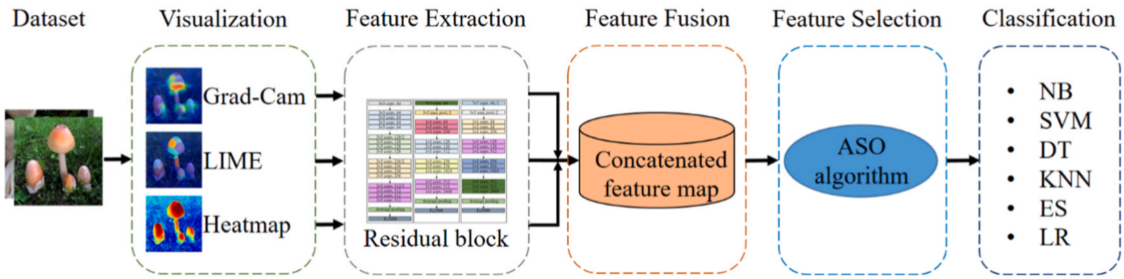

Fig. 1. Flow diagram of the proposed methodology.

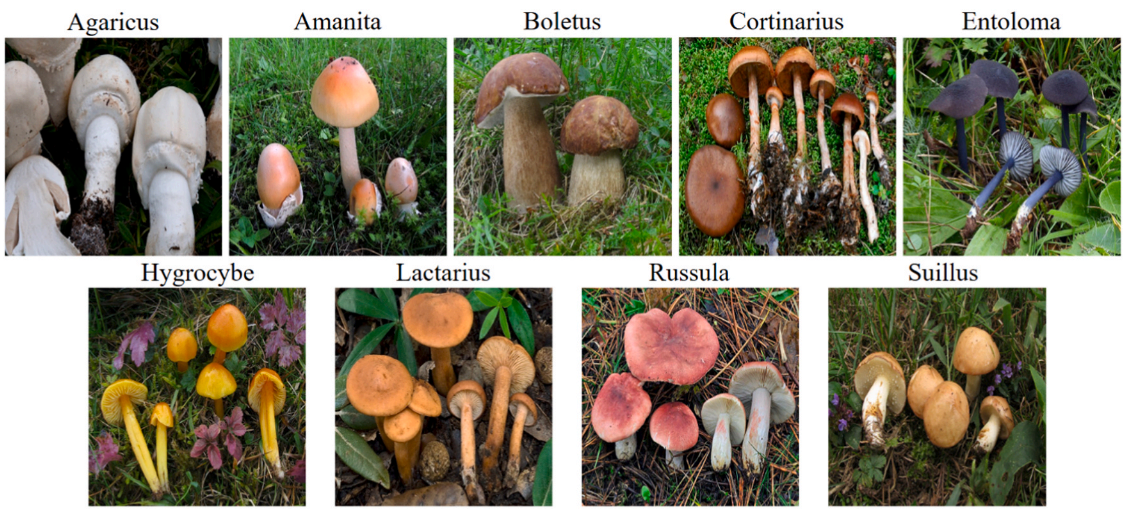

Fig. 2. Mushroom species dataset sample images.

making possible. Images of mushroom species were visualized using Grad-CAM, LIME, and Heatmap methods. The hybrid model developed for automatic mushroom classification used visualization images obtained using these three methods.

Using the Grad-CAM technique in deep learning classification techniques enables visualization of the model's attention on relevant image regions, aiding in understanding the decision-making process. This method also makes it feasible to comprehend the features that a classification model learns and the decision-making process involved. Grad-CAM is a visualization approach applied to CNNs. Although CNNs frequently produce accurate predictions, it might be challenging to comprehend the reasoning behind the model's selection. Thanks to Grad-CAM technology, it is now feasible to understand which aspects the CNNs choose to emphasize for each class. Gradients are used in the Grad-CAM visualization technique to identify the critical pixels for categorization. Grad-CAM creates feature maps for every class using gradient computing techniques. Subsequently, these feature maps are superimposed on the original picture to assist in pinpointing the decision-making region. Grad-CAM can be quickly and implemented in various neural networks because of its linear method foundation. Grad-

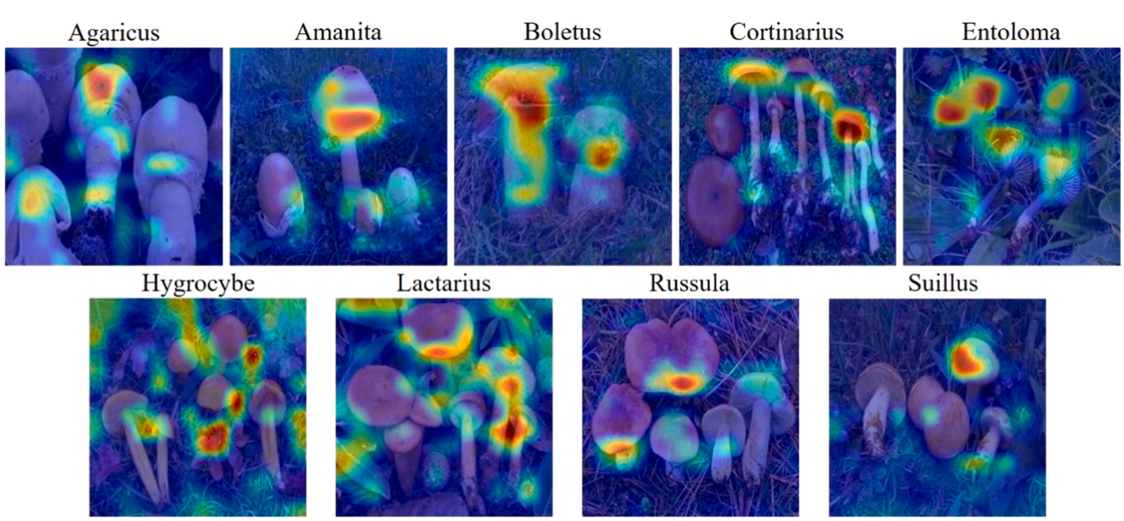

Fig. 3. Image visualization using the Grad-CAM method.

CAM maps the pixels connected to an object in the categorized image rather than using "bounding boxes" to indicate its location. It offers higher-quality, more precise, and detailed visuals in this way. Grad-CAM is helpful for various tasks, including segmentation, object detection, and picture classification. By doing this, we can obtain a significant edge in determining which features your model considers essential when making decisions [30]. Fig. 3 shows representative images of various mushroom species processed using the Grad-CAM method.

LIME is another method employed for image visualization. An annotation method called LIME provides context for ML models' decisions. This method is primarily intended for "black box" models, including intricate neural network models. To explain the model's prediction for a particular sample, LIME creates random samples and compares them with individual samples. The fraction of these samples is then used to calculate a quantifiable weight for every feature that influences the model's conclusion. These weights clarify how and why the model makes the judgments. Employing the LIME technique in deep learning classification facilitates the interpretation of model predictions by generating locally faithful explanations for individual predictions. In this regard, including the LIME technique in DL methods in areas where vital decisions are made, such as agricultural developments, can help improve the decision-making process. The parts of an essential image for a given class can be identified using LIME. Accuracy problems with classification can be resolved using this strategy. The areas of the image that are essential for classification are shown on the feature maps. The red areas show the regions in which the model is denser. Consequently, LIME uses data close to the input to be anticipated to build an explanatory model. The consequences of a few selected important features are explained in detail by this explanatory model. This makes it possible to gather details about which attributes, how they are influenced, and which regions are more susceptible to being impacted by the outputs of a complicated black box model. It can be used to clarify the rationale behind the forecasts and increase the transparency of the model's decision-making procedures [31]. Fig. 4 displays sample images produced by applying the LIME method to images of different mushroom species.

A Heatmap is a data visualization technique that shows the density or intensity of data using color gradients. This visually represents data patterns and trends, highlighting higher or lower-density areas. A density map shows higher or lower-density areas using color gradients or contour lines and provides information about patterns, clusters, and spatial trends. By analyzing the density map, researchers and decision-makers can make informed decisions, identify focal points, and effectively allocate resources. Heatmaps are widely used to understand and interpret vast and complex datasets. They show the data distribution on a two-dimensional plane, each cell representing a specific value. These cells are filled with colors, representing a particular range of data. A temperature color scale is often used to indicate the density of the data. For example, low values are represented by cool colors (e.g., blue), whereas high values are represented by warm colors (e.g., red). Middle values are usually expressed in colors such as green or yellow. Heatmap is another method employed for image visualization [32]. Fig. 5 displays sample images produced by applying the Heatmap method to images of different mushroom species.

Using Grad-CAM, LIME, and Heatmap methods to visualize the mushroom species images, the resulting pictures served as the foundation for the proposed model.

3.2. CNN, ASO, and classifiers

This paper employed CNN architectures, a deep learning sub-branch, to extract features automatically. One of the most well-known deep learning techniques, CNN architectures, was created so that computers could process text, audio, and image data. Activation functions, pooling layers, convolutional layers, and Softmax classification layers are typical components of a CNN architecture. In general, CNN architectures are divided into two sections. In the first section, features are extracted; in the second section, classification is performed. In the field of agriculture, CNN models have also become increasingly common.

This paper's automated classification of mushroom species images was based on ResNet architectures. Deep features were obtained from the images using Grad-CAM, LIME, and Heatmap methods, executed on the original dataset using ResNet architectures. The features obtained from these three methods were concatenated into a single feature map. The ASO algorithm was used to eliminate unnecessary features and highlight valuable features. ASO was used to select valuable features from the obtained feature map. When the data are highly dimensional, the ASO algorithm dimension reduction approach is used to identify the critical features in the dataset. This reduces the size of the dataset while selecting fewer significant features. The chosen attributes can adequately describe the dataset.

3.2.1. Residual block-based CNN

Even with more than 150 layers, ResNet can successfully deliver very successful training, and it comes in various models, including ResNet18, ResNet50, and ResNet101. There are many residual blocks in ResNet, and its models are constructed using these residual blocks as building blocks [33]. Each block comprises convolution and pooling layers, and they all operate using 224×224 pixel input images. The CNN models of ResNet18, ResNet50, and ResNet101 have 71, 177, and 347 layers,

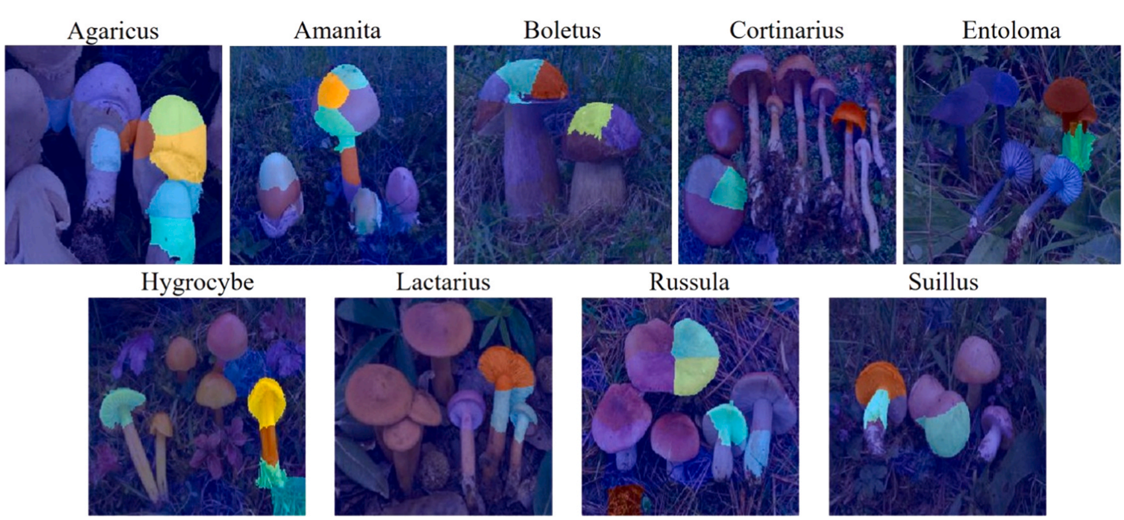

Fig. 4. Image visualization using the LIME method.

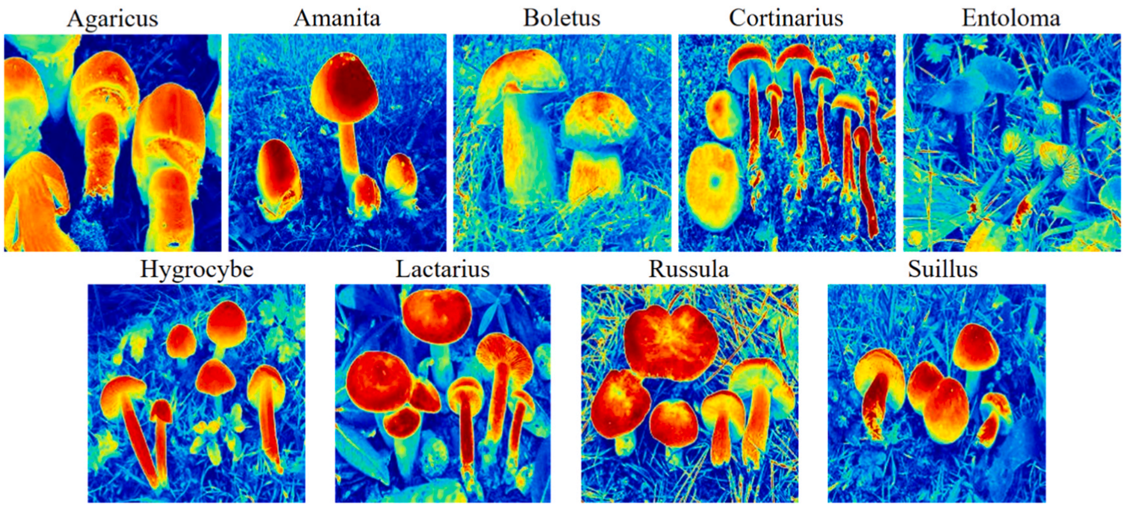

Fig. 5. Image visualization using the Heatmap method.

respectively [34]. A stack of layers configured to output one layer and add it to a layer further down the block is called a residual block. A residual connection is a straight line connecting the layer input (x) to the output. Residual connections can skip one or more tiers [35]. Eq. (1) displays the layer output formula following the residual connection

$$H(x) = f(wx + b) + x \tag{1}$$

Inputs can quickly spread across the remaining links between layers in residual blocks. In addition, bypassing levels makes learning comparable mappings in the network more accessible. The performance of CNN models starts to decline as the number of layers increases, and the network becomes deeper. To address this issue, residual block-based CNN models have been created. Residual block-based CNN models were employed because of the benefit of residual blocks. Fig. 6 displays the residual block-based CNN sample model.

3.2.2. ASO algorithm

Zhao et al. [36] presented the ASO method in 2019, a population-based metaheuristic optimization technique. In ASO, every atom's position in the search space has a solution that points to an atom that is either lighter or heavier than it. Every atom in the population either draws or repels every other atom. Light atoms seek space quickly for suitable solutions. Slow-moving heavy atoms look for favorable solutions in nearby space. Atoms must move forward toward the best atom i. Eq. (2) provides the atom's constraint formula:

$$Q_i(t) = \left[|x_i(t) - x_{best}(t)|^2 - b_{i,best}^2\right] \tag{2}$$

The location of the population's best atom in the $t.b_{i,best}^2$ iteration, and the fixed bond length between atom i and the population's best atom are shown by the $x_{best}(t)$ formula. Eq. (3) provides the constraint force formula [36]:

$$G_i^d(t) = \lambda(t)(x_{best}^d(t) - x_i^d(t)), \lambda(t) = \beta e^{-\frac{20t}{T}} \tag{3}$$

here $\lambda(t)$ is defined as the Lagrangian multiplier and β is the multiplier weight. Eqs. (4) and (5) provide the formulas for atoms' location and velocity vectors.

$$v_i^d(t+1) = rand_i^d v_i^d(t) + a_i^d(t) \tag{4}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{5}$$

Atoms in the ASO algorithm must interact with numerous atoms with fitness values as high as K to maximize discovery and exploitation. With every repetition, the K value decreases. Eq. (6) is used to obtain the K value.

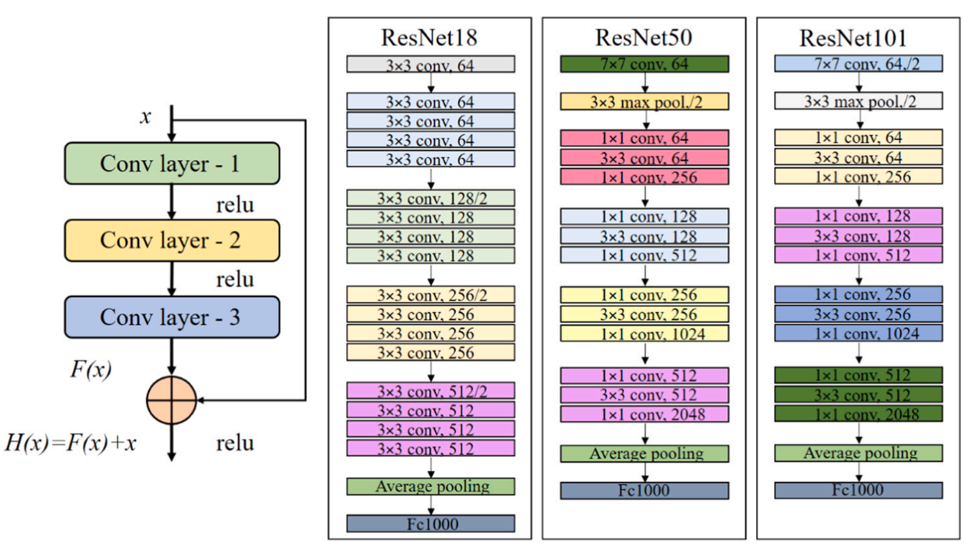

Fig. 6. Residual block illustration.

$$K(t) = N - (N-2) \times \sqrt{\frac{t}{T}} \tag{6}$$

where N is the total number of atoms, t denotes the number of iterations, and T denotes the maximum number.

Constrained engineering issues are well-solved using the population-based heuristic optimization technique known as the ASO algorithm. In addition, a great deal of research has produced positive outcomes in feature selection processes [37,38]. The following are the parameters of the ASO algorithm used for feature selection.

Algorithm 1. : ASO

Initial: $D = 1000$; (Dimension is the feature size of the Fc1000 layer of ResNet),
$N = 10$ (Solution Size),
Population x, (N, D); (each element of matrix x_i^d),
MaxIt = 100 (max iteration),
NFE = MaxIt × N; (Number of function evaluations=100×10 =1000),
th = 0.5; (Threshold value),
ho = 0.3; (Ratio of validation),
alpha = 50; (Depth weight),
beta = 0.2; (Multiplier weight),
The initial calculation of x, (N, D) was obtained randomly between $0 < x_i^d < 1$.
if ($x_i^d >$ th(0.5)) fitness values = 1;
else fitness values = 0;
The K-nearest neighbor (KNN) approach was used to determine the fitness of the solution matrix values created in each iteration. The KNN parameters are as follows:
K = 5;
alpha = 0.99;
beta = 0.01;
Calculation of fitness;

Eq. (7) is the formulation for the fitness calculation.

$$Fitness = alpha \times ErrorRate + beta \times (SF/D), EroorRate = 1 - ACC, SF = \sum_{i=0}^{D} x_i = 1 \tag{7}$$

Features obtained from three different ResNet models from Residual block-based CNN models were combined into a single feature map. Feature selection was applied to the resulting feature map using the ASO algorithm, depending on the alpha (0.99) and beta (0.01) values in the KNN. Selected features (*SF*) refer to the sum of selected features.

The ASO algorithm balances exploration and exploitation, facilitating a compelling exploration of diverse solution spaces while efficiently refining promising solutions. Its computational efficiency and scalability render it suitable for large-scale optimization problems, including those with high-dimensional or complex search spaces [39]. ASO's flexibility allows for easy customization to various optimization problems, while its global optimization capability enables comprehensive exploration for finding optimal solutions even in non-convex scenarios. With fast convergence properties and competitive performance in empirical studies, ASO emerges as a promising choice for optimization tasks across different domains, warranting comparison with other metaheuristic methods for specific problem contexts [40].

3.2.3. Classifiers

Algorithms and models called ML classifiers are used to categorize samples within a dataset. To process the dataset and categorize upcoming samples into appropriate groups, they use and gain knowledge from its attributes[41,42]. In this way is a sequenced explanation of the classifiers used in this paper:

Naive Bayes (NB): The Naive Bayes algorithm is an algorithm for classification and categorization bearing Thomas Bayes' name. Naive Bayes classification uses a set of computations specified by probability principles to identify the class or category of data fed into the algorithm. By using a particular probability distribution, the naive Bayes classifier determines how the properties of the inputs relate to the classes [43].

SVM: Among the supervised learning techniques frequently applied to classification issues is SVM. It creates a line to divide points on a plane. It aims to obtain the maximum distance for the points of both classes of this line. SVM is an effective classification technique, particularly in high-dimensional feature spaces. This is so that classes can be distinguished using a bounding plane selected by the kernel function used by the SVM, which first shifts the feature space to a low-dimensional subspace [44].

DT: A classification technique called decision trees builds a model as a tree structure with decision nodes and leaf nodes arranged by the feature and target. The dataset is divided into ever-tinier segments to construct the decision tree algorithm. One or more branches may be in a decision node. The root node is the initial node. Both numerical and categorical data can be included in a decision tree [45].

KNN: The most straightforward use of KNN is to estimate the class of the vector made up of the independent variables of the value to be predicted using the information about the class in which the nearest neighbors are concentrated. The KNN classifier is extensively employed, particularly in data mining and big data. Linear separability of the data is not a prerequisite for the KNN classifier. Furthermore, KNN does not require selecting any prediction model or parameter during the training, testing, and validation stages.

Ensemble subspace (ES): This classifier uses the KNN method to generate a classification model in each submature space after first dividing the data into submature spaces. The outputs of these submodels are then aligned and integrated. This approach seeks to improve classification performance by employing multiple submodels when data may behave differently in feature spaces with distinct structural

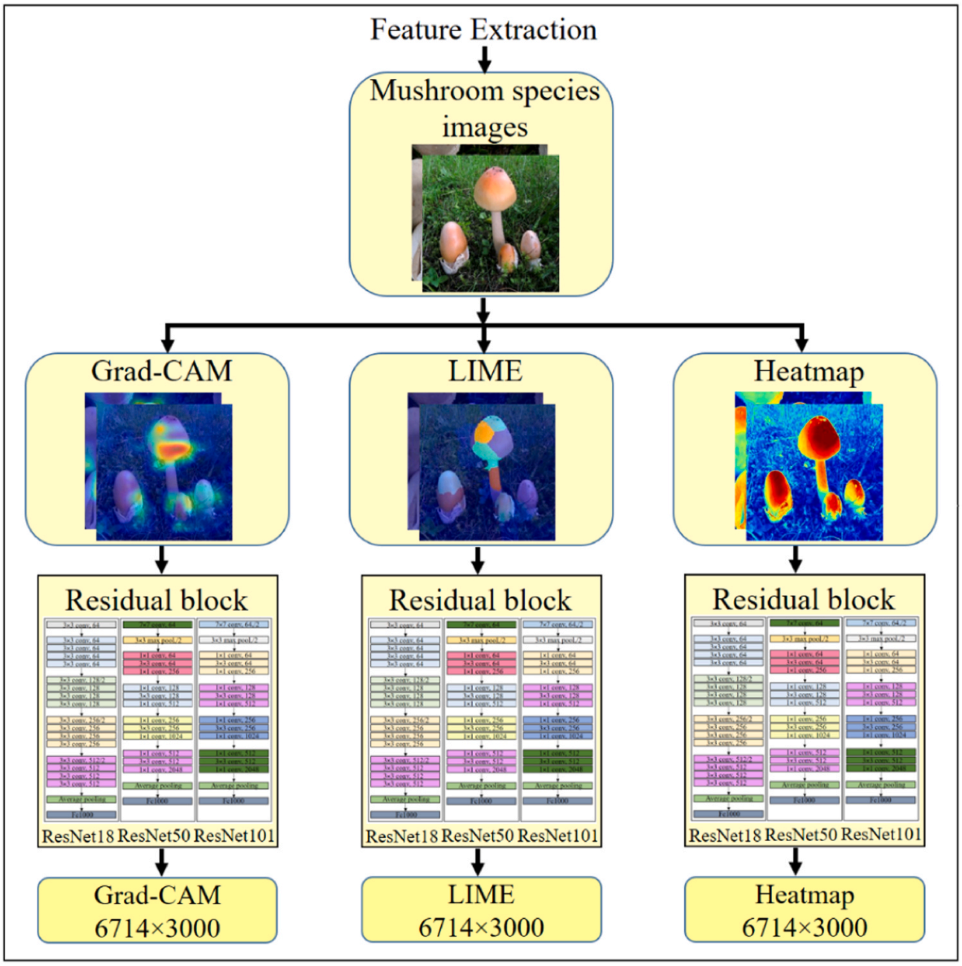

Fig. 7. Feature extraction process of the proposed model.

characteristics. This method is beneficial because it reduces the overfitting issue and shrinks the feature space, making it more scalable for higher-dimensional data [46].

Logistic regression (LR): LR is a method of data analysis that establishes connections between two data elements using mathematical principles. Logistic regression then uses this connection to forecast one of these components' values depending on the other. A prediction typically has two possible outcomes: yes or no. Normally, a linear regression model is used to perform the classification procedure. However, because the output value of linear regression is a continuous variable and cannot predict values outside of its constraints, it is not a suitable method for classification problems. Logistic regression classifies data using a linear regression model and assigns a class label to the resultant output [47].

3.3. Proposed model

In this paper, a novel model for the classification of mushroom species images was created. Residual block-based CNN models serve as the foundation for the produced model. CNN architectures automatically conduct feature extraction, whereas feature extraction is performed by a specialist using hand-crafted techniques. As a result, the proposed model uses feature extraction from the residual block-based CNN models' Fc1000 layers. The image visualization phase also increased the proposed model's performance metrics. Visualization of the images was generated using the Grad-CAM, LIME, and Heatmap methods. Using residual block-based CNN models, 6714×3000 size feature extraction was obtained from Grad-CAM-applied images,

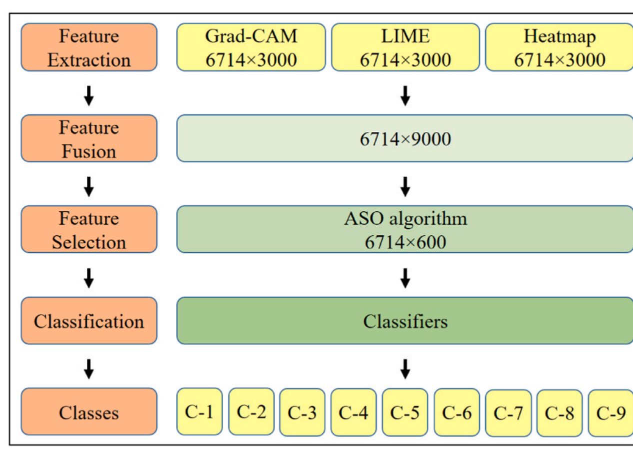

Fig. 8. Flow diagram of the proposed model.

6714×3000 size feature extraction was obtained from LIME-applied images, and 6714×3000 size feature extraction was obtained from Heatmap-applied images. Several aspects of the same image are emphasized in this phase. Fig. 7 illustrates the feature extraction procedure.

The 6714×3000 size feature extractions obtained from each Grad-CAM, LIME, and Heatmap method were concatenated as a single feature map in the feature fusion step using residual block-based CNN models. Following concatenation, the obtained feature map size was

6714×9000.

The ASO algorithm, a novel addition to the field, was a key component implemented in the feature selection step of the proposed model. This innovative approach, unique to our research, allowed the model to run faster and produce successful results. In this step, the size of the feature map was reduced using the ASO algorithm. Using the ASO algorithm, the feature map size was decreased to 6714×600. Combined with using six separate classifiers, this unique method led to the optimized feature map with a size of 6714×600 classified in the proposed model. Because there were nine classes of mushroom species in our study, in the last step of the proposed model, the relevant images were classified to be included in any of the nine classes. Fig. 8 shows the feature extraction, fusion, selection, and classification steps.

4. Results and discussion

Images of different mushroom species were automatically classified in this paper. A machine with a Core i7, 4.70 GHz processor, GTX4060Ti GPU, and 32 GB RAM was used to obtain the experimental results. All processes were performed in the Matlab environment. 80 % of the dataset was used for training, 20 % for testing, and all models produced results under the same conditions. Grad-CAM, LIME, and Heatmap methods were applied to the original mushroom species dataset to examine the performance of the proposed model. The visualization results obtained for each hand-crafted feature extraction were created independently of each other on the dataset. Residual block-based CNN architectures ResNet18, ResNet50, and ResNet101 were used to obtain the results of the original images of the mushroom species dataset. Since the most effective results obtained with the hand-crafted feature extraction method among different pre-training architectures are obtained from Residual block-based models, this study aims to improve the classification performance of the ASO optimization algorithm with the hybrid approach of varying visualization techniques in feature extraction using ResNet versions. Thus, a fair evaluation was made of the proposed model. 6714×1000 size feature maps were obtained using these CNN architectures. As shown in Fig. 9, a 6714×1000 feature map of each mushroom sample in the original dataset was obtained from the Fc1000 layer using residual block base CNN models. Then, these feature maps were classified using a diverse set of six different classifiers: NB, SVM, DT, KNN, ES, and LR. The experimental results are given in Table 1.

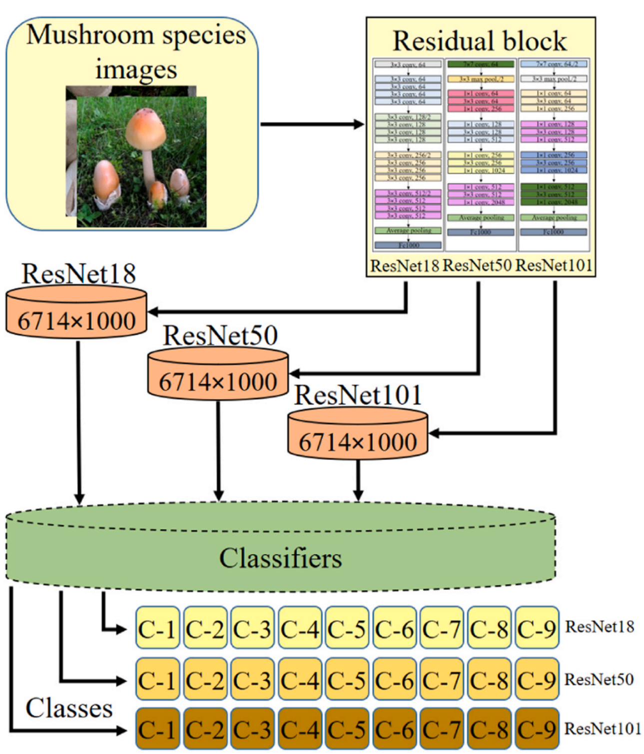

Fig. 9. Residual block-based CNN model flow diagram using the original dataset.

Table 1
Accuracy (%) results obtained from the original dataset.

	NB	SVM	DT	KNN	ES	LR
ResNet18	61.3	81.1	50.3	83.5	83.2	75.8
ResNet50	63.8	83.9	50.1	86.2	83.3	78.3
ResNet101	64.1	84.2	51.7	86.4	83.9	78.5

Table 2
GFLOPs results of the Residual block-based models.

Models	ResNet18	ResNet50	ResNet101
GFLOPs	1.82	3.87	7.69

Table 1 showcases the impressive accuracy values obtained from the original dataset, ranging from 50.1 % to 86.4 %. The highest accuracy value, 86.4 %, was obtained by combining the ResNet101 architecture and the KNN classifier using the original mushroom species dataset. This high level of accuracy demonstrates the effectiveness and reliability of the proposed model, instilling confidence in its potential for real-world application.

In Residual block-based learning for mushroom species classification, the results obtained for the ResNet models in terms of Giga Floating Point Operations per second (GFLOPs) with an input image size of 224×224 are given in Table 2. GFLOPs measure a model's computational complexity or workload, indicating how many billion floating-point operations the model performs per second during training. In the context of deep learning models like ResNet, GFLOPs estimate the computational cost required to process an input image through the network. Higher GFLOP values typically indicate higher computational requirements, influencing inference speed, memory usage, and hardware requirements for deploying the model.

In the residual block-based hybrid model proposed for the automatic detection of mushroom species, visualization results were first obtained from the raw dataset samples using Grad-CAM, LIME, and Heatmap methods. A total of 1000 features were extracted from the Fc1000 layer of each of the ResNet18, ResNet50, and ResNet101 architectures, with a size of 6714×3000 for each method. All extracted features were concatenated. In total, a single feature map of 6714×9000 size was obtained from the visualization results of these three methods. The size of the feature map optimized with the ASO algorithm was reduced from 6714×9000–6714×600. The optimized feature map using the ASO algorithm was finally classified using six classifiers. The proposed model works faster and more efficiently than the classification performed on the original dataset. The results of this study open up exciting possibilities for future research and development in mushroom species classification.

Considering the confusion matrices in Fig. 10, the highest classification success was achieved with the KNN classifier, while the lowest classification result was achieved with the DT classifier. The DT classifier predicted 700 correctly and 642 incorrectly out of 1342 mushroom species test images. KNN predicted 64 correctly and six incorrectly out of 70 test images belonging to the Agaricus mushroom species in class 1. In Class 2, out of 150 Amanita mushroom species test images, KNN predicted 143 correctly and seven incorrectly. In Class 3, out of 214 test images of the Boletus mushroom species, KNN predicted 206 correctly and eight incorrectly. In Class 4, out of 167 test images of the Cortinarius mushroom species, KNN predicted 159 correctly and eight incorrectly. In Class 5, out of 73 Entoloma mushroom species test images, KNN

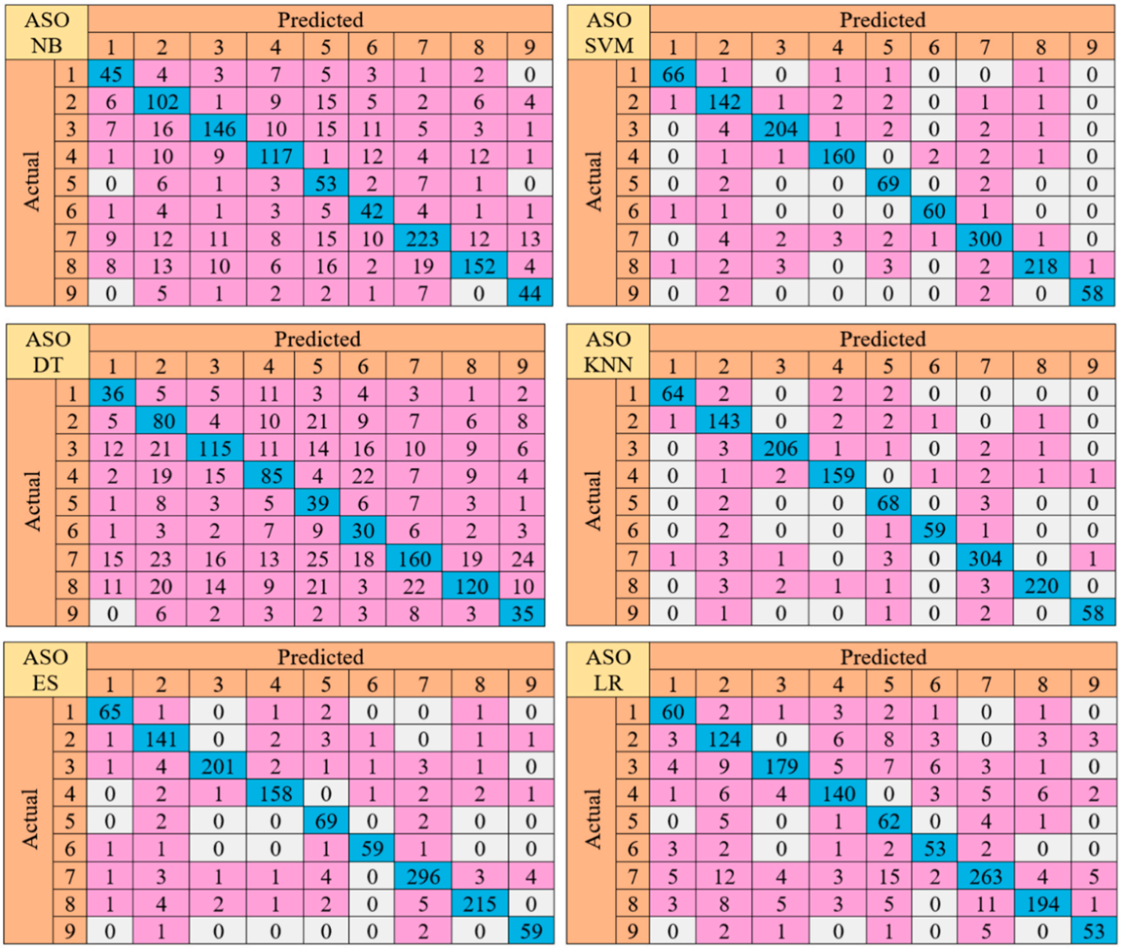

Fig. 10. Confusion matrix of the proposed model.

Table 3
Accuracy (%) results obtained using the proposed model.

	NB	SVM	DT	KNN	ES	LR
Proposed model	68.85	95.15	52.16	95.45	94.11	84.05

predicted 68 correctly and five incorrectly. In Class 6, out of 63 test images of the Hygrocybe mushroom species, KNN predicted 59 correctly and four incorrectly. In Class 7, out of 313 Lactarius mushroom species test images, KNN predicted 304 correctly and nine incorrectly. In Class 8, out of 230 test images of the Russula mushroom species, KNN predicted 220 correctly and 10 incorrectly. In Class 9, out of 62 Suillus mushroom species test images, KNN predicted 58 correctly and four incorrectly. The KNN classifier, which achieved the highest classification success, predicted 1282 of 1342 images correctly and 61 incorrectly. Thus, the KNN classifier achieved the highest success rate of the proposed model with an accuracy value of 95.45 %. Among the classifiers used to classify images of different mushroom species, the KNN technique proved the most effective because of its easy, understandable, and straightforward classification methodology. KNN is simpler to use and comprehend than other sophisticated ML algorithms' training and implementation procedures. Since KNN does not make any assumptions or biases during its predictions, it offers a versatile classification method, considering that images of different mushroom species can show complexity and variability. The accuracy results obtained using the proposed residual block-based hybrid model, optimized with the ASO algorithm, using six ML classifiers are given in Table 3.

Table 4 presents the results of the class-based performance evaluation metrics of the proposed hybrid method using the KNN classifier.

As shown in Table 4, the proposed model optimized with the ASO algorithm achieved maximum accuracy at class 7 with the KNN classifier. The accuracy value obtained in this class was 97.12 %. On the other hand, class 1 has the lowest accuracy result obtained using the proposed model with the KNN classifier. The accuracy value obtained from this class was 91.42 %, the group with the least successful classification.

Table 4
Evaluation metrics of the proposed model using KNN classifiers (%).

Classes (1−9)	1	2	3	4	5	6	7	8	9
Accuracy	91.42	95.33	96.26	95.20	93.15	93.65	97.12	95.65	93.54
Sensitivity	96.96	89.37	97.63	96.36	86.07	96.72	95.89	98.65	96.66
Specificity	99.52	99.40	99.29	99.32	99.60	99.68	99.12	99.10	99.68
F1-score	94.11	92.25	96.94	95.78	89.47	95.16	96.50	97.13	95.08
FPR	0.47	0.59	0.70	0.67	0.39	0.31	0.87	0.89	0.31
FDR	8.57	4.66	3.73	4.79	6.84	6.34	2.87	4.34	6.45
FNR	3.03	10.62	2.36	3.63	13.92	3.27	4.10	1.34	3.33

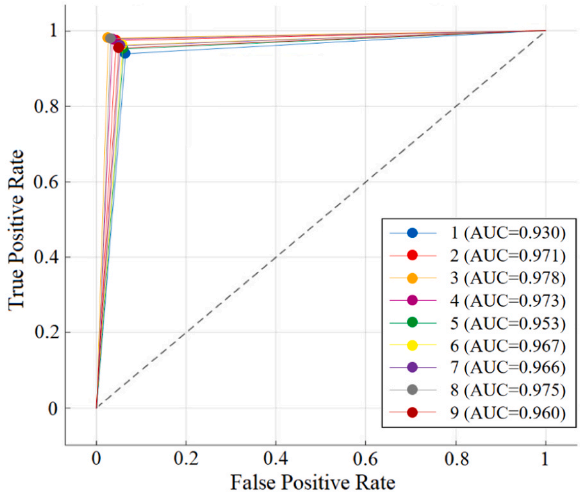

Fig. 11. AUC/ROC curves of the residual block-based hybrid model with the KNN classifier.

Table 5
Comparison of the proposed method with existing methods.

Study	Method	Class	Year	Accuracy
Lidasan et al. [21]	Segmentation GrabCut	Multi	2018	92.00 %
Kang et al. [20]	AlexNet, VGGNet, and GoogLeNet	2	2018	82.63 %
Ottom et al. [19]	KNN	2	2019	94.00 %
Sulc et al. [17]	Inception-v4	Multi	2020	52.60 %
Shuaichang et al. [48]	FGVT visual classification	Multi	2020	92.17 %
Ketwongsa et al. [23]	AlexNet, ResNet-50, and GoogLeNet	2	2022	95.50 %
Peng et al. [18]	M-Vit CNN	Multi	2023	91.83 %
Proposed model	Residual block-based CNN+ASO+KNN	Multi	2024	95.45 %

Fig. 11 displays the AUC/ROC curve produced by the proposed residual block-based hybrid model with the KNN classifier.

Evaluation of the produced models is essential to understanding their robustness in ML production lines. At this point, the ROC curve and AUC are frequently used metrics in the evaluation step of multi-class classification problems. The proposed residual block-based hybrid model demonstrated a high level of performance, as shown in Fig. 11.

The study's hybrid model outperformed similar research, and pre-trained models were approved in the literature regarding results. Comparable research on the classification of images of different mushroom species can be found in the literature. Table 5 presents studies on the classification of mushroom images.

In this paper, it has been shown that mushroom species identification from mushroom images can be performed with a high success rate using the learning method of pre-trained CNN architectures. It has been demonstrated that the Grad-CAM, LIME, and Heatmap visualization methods used In this paper contribute positively to revealing distinct and different features in classifying mushrooms viewed in their natural environment using deep learning methods. Moreover, it has been observed that the ASO algorithm, a metaheuristic optimization algorithm, contributes positively to the success of automatic mushroom species detection in optimizing the feature maps obtained with residual block-based architectures. Mushroom species samples visualized using Grad-CAM, LIME, and Heatmap methods achieved the highest classification accuracy result of 95.45 % with the combination of the residual block-based hybrid model, ASO algorithm, and KNN classifier. This significant result shows that pre-trained networks provide reasonable solutions to similar problems when selecting the transfer learning method appropriate to the problem, data, and network. Another critical study result is that the mushroom cap and body, which have many identifying features, play a crucial role in mushroom identification. In addition, it was concluded that taking photos from several mushrooms, rather than taking many photos from one, is much more critical regarding network performance.

Considering that the available data are limited, the number of samples is insufficient, and species diversity is obtained from multiple photographs obtained from a smaller number of mushrooms, this visual species identification is highly successful and proves to be an excellent forward-looking solution. Such research is vital for carrying mushrooms into the future. This is a problem solution that can be useful in protecting mushrooms, making sustainable management plans for mushroom resources, detecting poisonous mushrooms, mushroom cultivation, and classifying mushrooms according to mushroom types for mushroom pickers.

Several potential limitations could affect the performance of a proposed hybrid model for mushroom species classification. Suppose the dataset used to train the model contains significantly more examples of certain mushroom species than others. In that case, the model may exhibit bias toward the overrepresented classes and struggle to classify the underrepresented ones accurately. If certain species exhibit variations in color, shape, or other features not well-represented in the dataset, the model may struggle to generalize to unseen examples. If the features used by the model are not sufficiently discriminative or if there is ambiguity in the labeling of training data, the model's performance may suffer. Some mushroom species may closely resemble species from other classes, making accurate classification difficult. These cases of morphological similarity can confound the model's ability to differentiate between classes. The dataset used to train the model is small or lacks diversity; the model may struggle to learn robust representations of mushroom features, leading to poor generalization performance on unseen data. Depending on the complexity of the chosen model architecture and the dataset size, there may be a risk of overfitting, especially if the model has many parameters relative to the amount of training data available. Addressing these limitations may involve collecting more diverse and balanced datasets, carefully selecting informative features, augmenting training data to increase variability, regularizing model training to prevent overfitting, and conducting thorough validation and testing on unseen data.

One of the main aims of this paper is to contribute to solving the problem of lack or inadequacy of the dataset encountered in identifying mushroom species from mushroom images. However, considering the number of mushrooms on earth and their diverse environments, expanding the dataset is far from a one-person effort. It is a team effort and a process that will continue for many years. After this paper, it is planned to develop the paper and make it available to the public with a project that covers more mushroom species in the literature.

5. Conclusion and future work

This paper proposes a new hybrid method for the efficient and automatic classification of nine different wild mushroom species found in nature. In the proposed system, samples of various mushroom species were visualized using the Grad-CAM, LIME, and Heatmap methods. As a result, a hybrid model was developed that concatenates high-level feature information with low-level mushroom species traits to enhance the effect of fine-grained recognition. Our methodology combined wild mushroom images' planar and spatial information with the visualization methods used and parsed the spatial axis information. Thus, the network benefited from the different features of the same image. The multidimensional feature map obtained by combining various features was optimized and reduced in size using the ASO algorithm to reduce computational complexity and separate spatial axis information. A new residual block-based hybrid method is proposed to detect fungal species automatically. It has been shown that the hybrid model optimized with the proposed ASO algorithm effectively classifies images of mushroom species. The proposed residual block-based hybrid model achieved a classification result with an accuracy value of 95.45 % with the combination of the ASO algorithm and the KNN classifier. Factors such as data quality, class overlap, feature limitations, model complexity, risk overfitting the training data, limitations of algorithms such as ASO and KNN used in the training and test dataset, generalization error, randomness, and variability in data collection, model evaluation metrics, and validation these are among the reasons that directly affect classification efficiency. These factors collectively contribute to the difficulty of achieving complete accuracy. Instead, the goal is often to balance high accuracy and the model's ability to generalize well to new data. This result proved the proposed hybrid method's practical and easy applicability for categorizing mushroom species images. Moreover, it has been shown that with the proposed model, an effective and high-accuracy result can be achieved with low computational cost, even in a dataset containing some mushroom species images.

Ethical approval

None of the authors conducted human or animal studies.

CRediT authorship contribution statement

Erdal Özbay: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Feyza Altunbey Özbay:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Farhad Soleimanian Gharehchopogh:** Writing – review & editing, Project administration, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data availability

The data that has been used is confidential.

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