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Research Article

Deep Learning and Machine Learning Comparison for Korean Wild Medicinal Mushrooms

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Abstract
In classifying Korean wild mushrooms as medicinal or non-medicinal, stem size, spore size, ecological status, and occurrence seasons were strongly significant. On the other hand, cap size and geometric features such as longitude, latitude, and altitude of the photo images taken were not significant. With these tabular measurement datasets, machine learning models, especially Linear Discriminant Classification, outperform the RexNet150-based deep learning model in terms of accuracy and F1 score. The resulting test set accuracy rate of Linear Discriminant is 0.941. However, the test set accuracy rates for machine-learning and deep-learning classification of poisonous and edible mushroom species are low, at 0.65 and 0.68, respectively. Morphologically and ecologically, Korean medicinal wild mushrooms are relatively small in stem and spore size, occur more frequently during winter and spring, and are more likely to be saprotrophic.
Keywords: Medicinal, Edible and Poisonous Mushrooms, RexNet150, ANOVA, PCA, Machine Learning, Linear Discriminant Classification, Deep Learning.

1. Introduction

Recent studies show that image-based deep learning, ensemble learning, and explainable AI are increasingly effective for mushroom classification. In contrast, statistical and traditional machine learning methods remain useful as baselines and for feature-driven interpretation [1]. This study tries to contribute to the mushroom classification literature by integrating deep learning, machine learning, and statistical analysis to distinguish Korean wild medicinal and non-medicinal mushrooms, while also evaluating the more challenging edible-versus-poisonous classification problem in a real-world Korean wild mushroom setting [1].

2. Literature Review

Mushroom identification has become an important research topic because misclassification can pose serious food safety risks, especially when edible species are mistaken for poisonous ones [2]. In parallel, medicinal mushrooms have attracted interest for their bioactive compounds and functional properties, whereas non-medicinal mushrooms are often studied primarily for taxonomy, ecology, or edible safety [3]. These two directions have motivated recent studies to move beyond simple manual identification toward data-driven classification systems that can support safer and more reliable mushroom assessment [2]. Early work in mushroom classification relied heavily on traditional machine learning methods trained on morphological or tabular features. Comparative studies show that models such as decision trees, support vector machines, random forests, and k-nearest neighbors can provide useful baselines. Still, their performance is often lower than that of deep learning models at high visual complexity [4]. This suggests that classical approaches are still valuable for feature engineering and statistical interpretation. Still, they may be limited in their ability to capture subtle variations in texture, shape, and color among closely related mushroom species [5].

With the growth of image datasets and computing power, deep learning has become the dominant approach for mushroom classification. Convolutional neural networks have been applied to edible-versus-poisonous classification, with studies reporting better performance than traditional methods, particularly when transfer

learning and hyperparameter tuning are used [5]. A Vision Transformer-based study also reported strong results for mushroom species classification, showing that transformer architectures can handle fine-grained visual distinctions effectively and may outperform CNN-based pipelines in some settings [2]. These findings support the use of deep models in our paper, especially when the classes are visually similar and the dataset contains heterogeneous field images.

Research on wild poisonous and edible mushrooms is especially relevant to our second task. Recent studies have shown that high-performing CNNs and ensembles can classify wild poisonous species with strong accuracy, and that ensemble learning often improves robustness over single models [1]. For example, explainable deep learning frameworks based on EfficientNet, DenseNet, MobileNet, and ShuffleNet variants have achieved high accuracy and strong reliability metrics, while also using Grad-CAM or related tools to show that the model's attention aligns with biologically meaningful regions [1]. However, earlier work with smaller or more challenging datasets reported more modest accuracy, indicating that mushroom classification remains sensitive to dataset quality, class balance, and environmental variation [6].

A related line of research has examined mushroom safety using spectral data and statistical learning rather than images. One study on wild porcini mushrooms used FT-NIR spectroscopy and compared deep learning models, which produced excellent recognition performance and could also support geographic traceability [7]. This is important for our study because it shows that statistical analysis is not only useful for model comparison, but also for understanding biochemical or regional differences that may separate mushroom groups beyond visible morphology [7]. Such work supports hybrid research designs that combine statistical analysis with machine learning and deep learning.

For medicinal versus non-medicinal, the literature is less standardized than for edible-versus-poisonous classification, but the broader mushroom literature still provides a useful foundation [3]. Medicinal mushrooms are often distinguished by their biological activity, bioactive compounds, and taxonomic identity, whereas non-medicinal species are more often characterized by ecology or general morphology [3]. This implies that distinguishing medicinal from non-medicinal wild mushrooms may benefit from a combination of visual features, metadata, and statistical testing, especially if the medicinal category includes species with external appearances similar to non-medicinal counterparts.

A key trend in recent studies is the use of explainable AI to improve trust and interpretability. Researchers have increasingly used Grad-CAM, LIME, t-SNE, and similar methods to show which image regions or feature embeddings drive classification decisions [8]. This is especially important in mushroom safety applications, where false negatives can have serious consequences, and users need more than a high accuracy score to trust the model [2].

Overall, the literature suggests three main points relevant to our paper. First, deep learning is highly effective for mushroom image classification, especially in distinguishing edible from poisonous species [2]. Second, traditional machine learning and statistical analysis remain important for benchmarking, feature interpretation, and identifying group differences that may not be visible in raw accuracy results [7]. Third, the classification of Korean wild mushrooms as medicinal versus non-medicinal is a promising yet comparatively underexplored area, making our study useful as a bridge among functional mycology, food safety, and data-driven taxonomy [3].

We are framing our investigations as a multi-level comparative study that extends mushroom classification in two directions: functional classification (medicinal vs. non-medicinal) and safety classification (edible vs. poisonous). We can also emphasize that our lower performance on the edible-versus-poisonous task is consistent with prior work showing that wild mushrooms are difficult to distinguish when their morphologies overlap or when datasets are limited [6]. That makes our statistical and machine learning comparison especially valuable because it helps explain where the model succeeds and where it struggles [5].

3. Functional Classification: Medicinal or Not

The original dataset is in text form, including image and measurement information, constructed from 2013 to 2026 by various researchers.[1] From these texts, morphological characteristics such as spore sizes and stem sizes are converted into tabular format. The locations of photos are converted to longitude, latitude, and

[1] https://www.nihhs.go.kr/mushroom/; https://www.naturing.net/m/911/entryobs/931/map

altitude. Moreover, the observation seasons are converted into zero-and-one dummy variables. The ecological status is given three numerical values. Finally, 18 numerical explanatory variables with 2 dependent variables, one measuring edibility and the other measuring medicinal effect, are constructed. Table 1 shows part of the summary statistics for this measurement dataset. Among 179 mushroom species, 20 are classified as medicinal, as shown in Figure 1. The remaining 159 mushroom species are classified as poisonous or edible but not medicinal.

Table 1. Part of summary statistics.

	Cap(min)mm	Cap(max)	Stem_Length(min)	Stem_Length(max)	Stem_Thickness(min)milimeter	Stem_Thickness(max)	Spore_Length(min)micrometer
count	179.000000	179.000000	179.000000	179.000000	179.000000	179.000000	179.000000
mean	37.790503	103.530726	36.145251	81.357542	6.605587	15.060335	8.111732
std	24.282674	73.191245	28.875773	61.547694	8.195029	19.381517	3.720566
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	3.000000
25%	20.000000	55.000000	20.000000	45.000000	2.000000	3.250000	6.000000
50%	30.000000	100.000000	30.000000	80.000000	5.000000	12.000000	7.500000
75%	50.000000	120.000000	50.000000	120.000000	10.000000	20.000000	9.500000
max	150.000000	600.000000	150.000000	300.000000	80.000000	200.000000	28.000000

3.1. ANOVA for Medicinal or Not

Based on the output in Tables 8-18 in the appendix, the simplified characteristics are summarized in Figure 2 after deriving mean values for spore length and related parameters, as well as the ratios of medicinal to non-medicinal mushrooms.

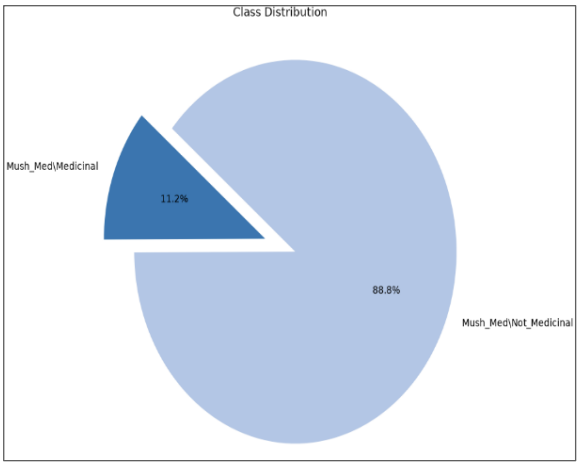

Figure 1. Pie chart: Medicinal or not.

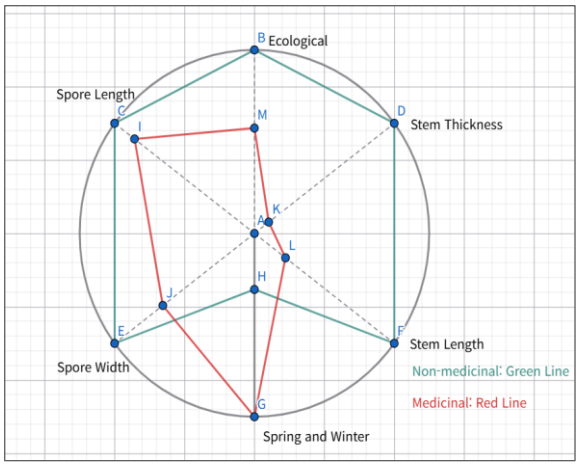

Figure 2. Graphical summary of medicinal or not.

Specifically, according to Figure 2, medicinal mushrooms have relatively small spores and stems. The ratios of medicinal mushrooms to non-medicinal mushrooms are 0.791, 0.615, 0.1916, and 0.06239 for spore length, spore width, stem length, and stem thickness, respectively, when the mean values of minimums and maximums are used. Moreover, medicinal mushrooms are more likely to be saprotrophic (0: Saprotrophic; 1: Mycorrhizal; 2: Parasitic). The mean value of ecological status of medicinal mushrooms is 0.3, while that of non-medicinal mushrooms is 0.629. In addition, medicinal mushrooms appear more frequently in spring and winter, with the sum of spring and winter dummy variables of 0.45, which is greater than 0.125 for non-medicinal mushrooms.

3.2. PCA for Medicinal or Not

To capture the relationships among features, the PCA biplot is shown in Figure 3 below.

The PCA biplot in Figure 3 shows two clusters: one of spore sizes and the other of stem sizes, both of which are negatively correlated with the medicinal dummy variable, consistent with the ANOVA results. The relative influence of cap size is smaller than that of stem size and spore size, which is consistent with the ANOVA results attached in the appendix. Medicinal mushrooms are positively correlated with longitude and latitude but are almost uncorrelated with altitude. However, these geographic relationships with the presence of medicinal mushrooms, in terms of the locations where photo images are taken, are not very strong, as observed in the

ANOVA models. There is no convincing evidence that longitude, latitude, and altitude differ between medicinal and non-medicinal mushroom species.

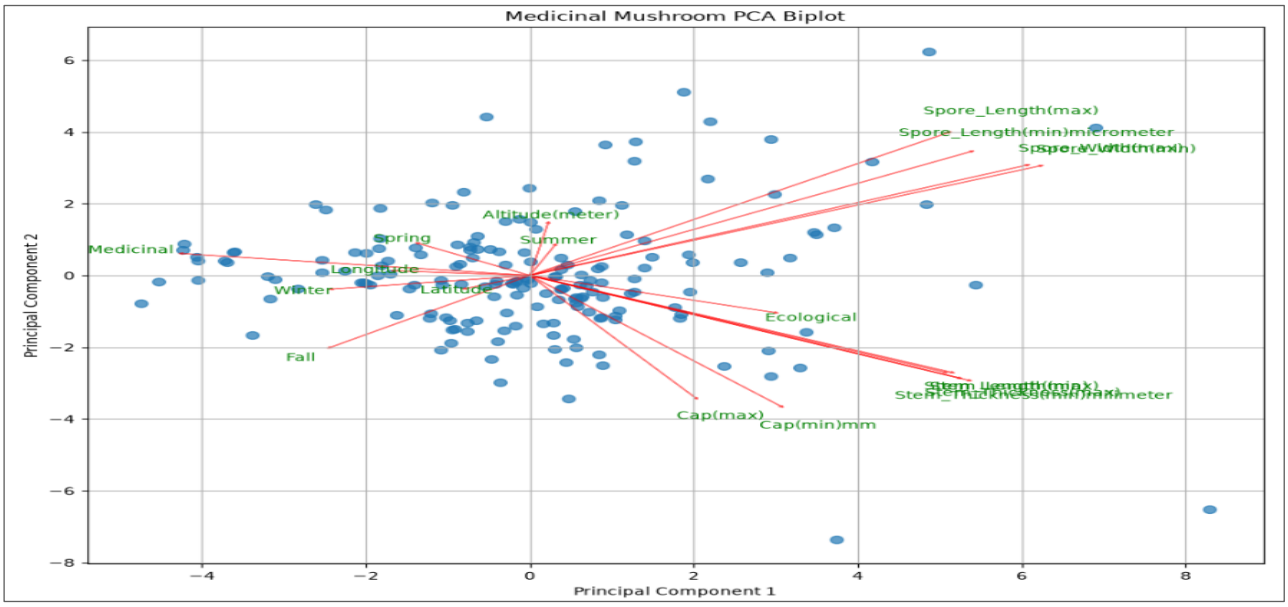

Figure 3. PCA biplot with medicinal dummy variable.

3.3. Machine Learning for Medicinal or Not

Using the same measurement datasets, 8 machine learning models for classifying medicinal versus non-medicinal are compared for accuracy, precision, recall, and F1 score, as shown in Table 2. Linear discriminant analysis (LDA) exhibits the best performance, followed by random forest classification (RF). Firstly, LDA assumes that classes are approximately linearly separable and that each class has a roughly Gaussian distribution with similar covariance structure [9]. More specifically, if chemical, morphological, or spectral features align with known discriminants such as cap, stem, and spore traits, LDA can capture the main direction of separation very effectively [9]. Secondly, RF is known to perform well on mushroom classification tasks, as it captures possible non-linear relationships through tree splits, even though the overall problem is likely mostly linear [9].

Table 2. Performance measures of classification in medicinal or not.

	Accuracy	Precision	Recall	F1
Boosting	0.857	0.841	0.857	0.848
Support vector machine classification	0.886	0.834	0.886	0.859
Neural network classification	0.857	0.735	0.857	0.791
K-nearest neighbors classification	0.886	0.886	0.886	0.886
Linear discriminant classification	0.941	0.946	0.943	0.929
Naïve Bayes classification	0.886	0.962	0.886	0.911
Decision tree classification	0.857	0.735	0.857	0.791
Random forest classification	0.914	0.932	0.914	0.922

Attached to this outcome, two confusion matrices are given in Tables 3 and 4.

Table 3. Confusion matrix from linear discriminant classification.

		Predicted	
Observed		**0**	**1**
	0	32	0
	1	2	1

Table 4. Confusion matrix from random forest classification.

		Predicted	
Observed		**0**	**1**
	0	29	3
	1	1	2

When comparing feature importance as measured by mean dropout loss in Tables 5 and 6, LDA appears to use more features, such as ecological, altitude, and winter and spring dummy variables, resulting in better performance.

Table 5. Feature importance from linear discriminant classification.

Variables	Mean dropout loss
Maximum of spore width	0.417
Minimum of stem length	0.414
Maximum of stem thickness	0.400
Minimum of cap	0.351
Ecological	0.344
Maximum of spore length	0.338
Altitude	0.321
Winter	0.319
Summer	0.317
Spring	0.313

Table 6. Feature importance from random forest classification.

Variables	Mean dropout loss
Minimum of stem length	0.200
Minimum of stem thickness	0.176
Maximum of stem thickness	0.169
Maximum of cap	0.150
Maximum of stem length	0.135
Minimum of spore width	0.127
Minimum of stem length	0.200
Minimum of spore width	0.127
Maximum of spore width	0.122
Longitude	0.092

3.4. Deep Learning for Medicinal or Not

Using the image datasets, part of which are shown in Figures 4 and 5, a RexNet150-based deep learning model is applied, achieving a test set accuracy of around 0.778 and an F1 score of around 0.875 for the best model saved, as shown in Figures 7 and 8. Early stopping is triggered with a patience level of 5 over 50 epochs.

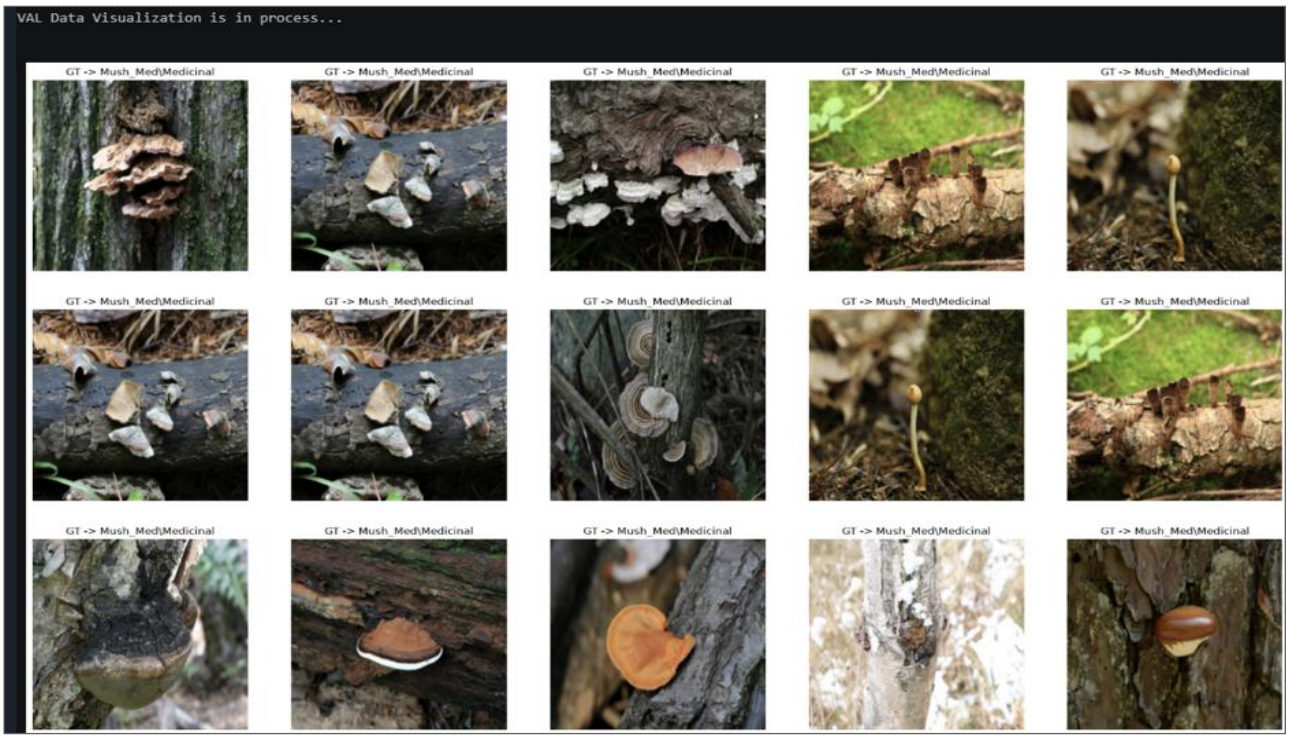

Figure 4. Part of medicinal mushrooms.

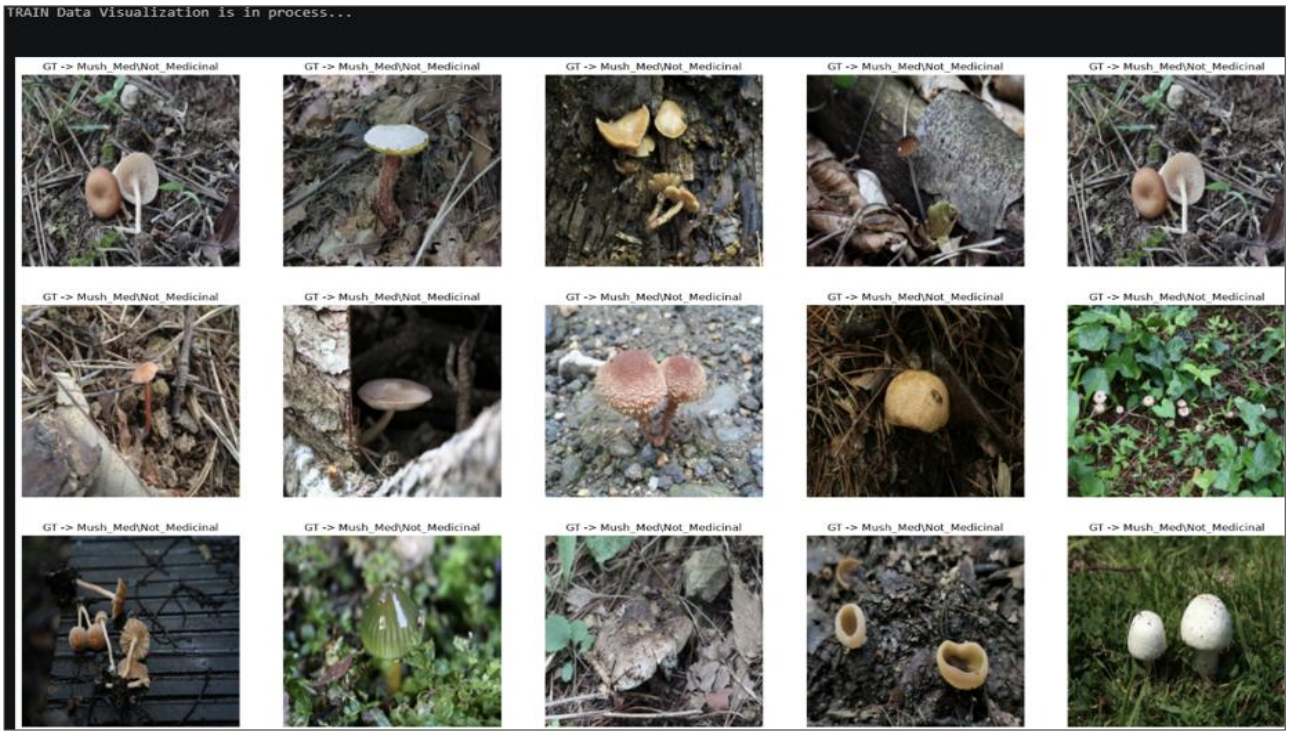

Figure 5. Part of non-medicinal mushrooms.

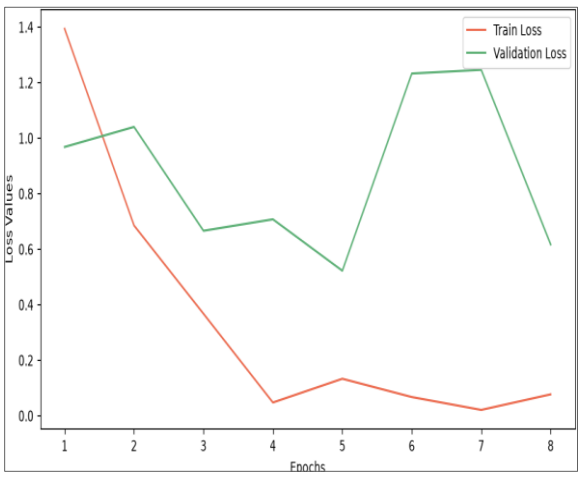

Figure 6. Plot of loss.

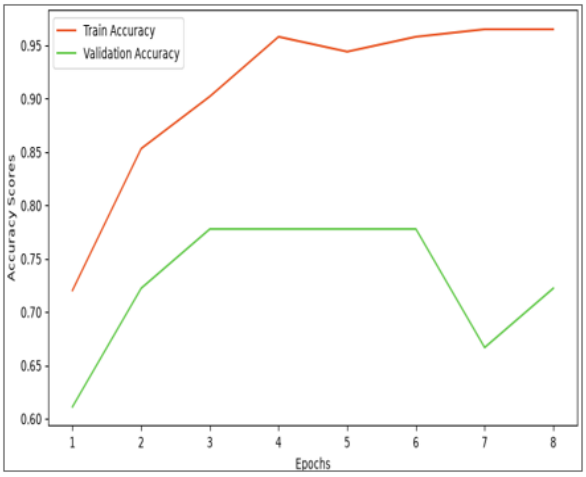

Figure 7. Plot of accuracy.

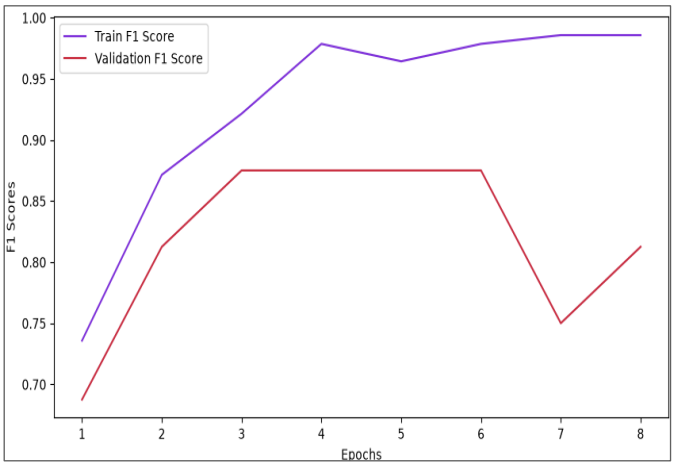

Figure 8. Plot of F1 score.

This result, that measurement data-based machine learning models outperform image-based deep learning models, can be explained by the fact that medicinal vs non-medicinal is fundamentally a biochemical and

pharmacological property, not purely a visual one [10]. That is, if our measurement data coincide with biochemical or pharmacological variables, these features are closer to the true decision boundary than RGB pixel patterns [10].

4. Safety Classification: Edible or Poisonous

Using the same procedures, ANOVA, PCA, machine learning, and deep learning models are applied to capture differences between edible and poisonous mushrooms.

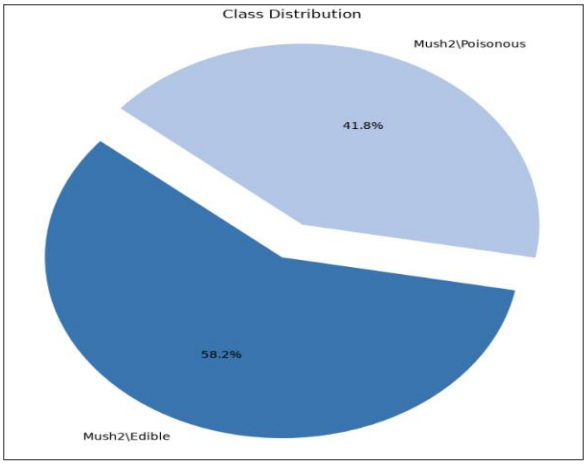

Figure 9. Ratio of edible mushrooms.

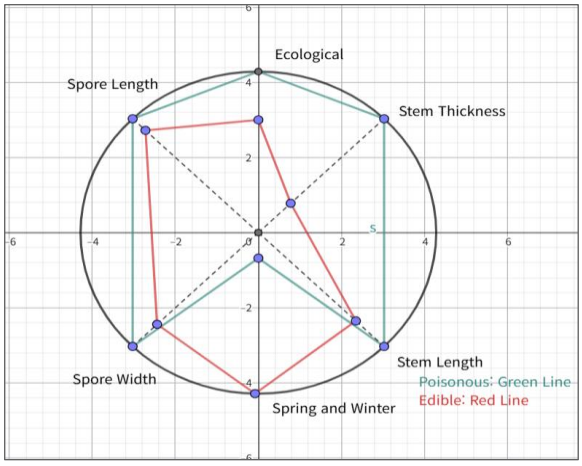

Figure 10. Graphical summary of edible vs poisonous.

As a summary of the outcomes from Tables 19-29 in the appendix, Figure 10 depicts the differences between poisonous and edible mushrooms. Like the characteristics observed in Figure 2, edible mushrooms appear relatively more frequently during the winter and spring, while exhibiting relatively smaller spore and stem sizes. In terms of numeric values, the mean value of the sum of winter and spring dummy variables is 0.238 for edible mushrooms, while it is 0.054 for poisonous mushrooms. The ratios of edible to poisonous mushrooms are 0.8727, 0.7750, 0.76, 0.30, and 0.654 for spore length, spore width, stem length, stem thickness, and the ecological dummy variable, respectively. When comparing Figures 2 and 10, the medicinal mushrooms are smaller than both the poisonous and the edible, but not medicinal, mushrooms.

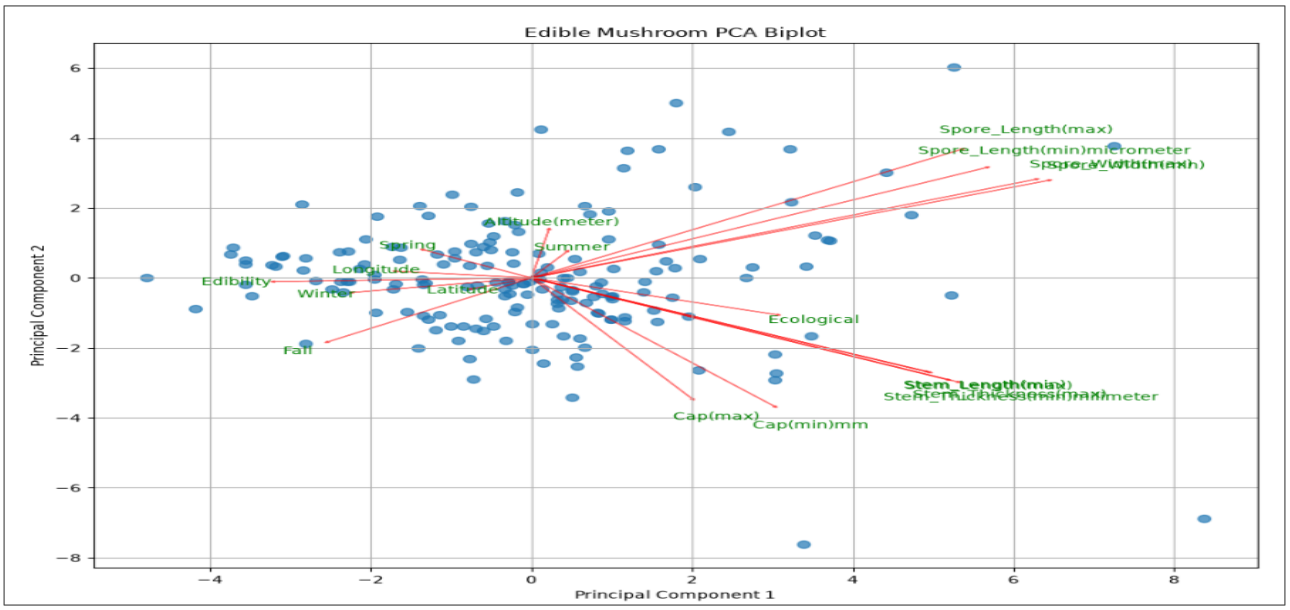

Figure 11. PCA biplot with edible dummy variable.

Compared with the PCA biplot in Figure 3, the relations between features are similar, except that the relative influence of the edible dummy variable on the second principal component is relatively weaker than that of the medicinal dummy variables, which might be the main cause of the relatively lower performance of machine learning classification.

Using the same dataset, a RexNet150-based deep learning classifier for distinguishing edible from poisonous mushrooms achieved around 68 percent accuracy and 75 percent F1 score, which is not satisfactory. Machine learning-based classification is more frustrating, with accuracy ranging from 0.371 to 0.657, as shown in Table 7. Linear Discriminant Classification outperforms other models, as in the case of classifying whether it is medicinal or not.

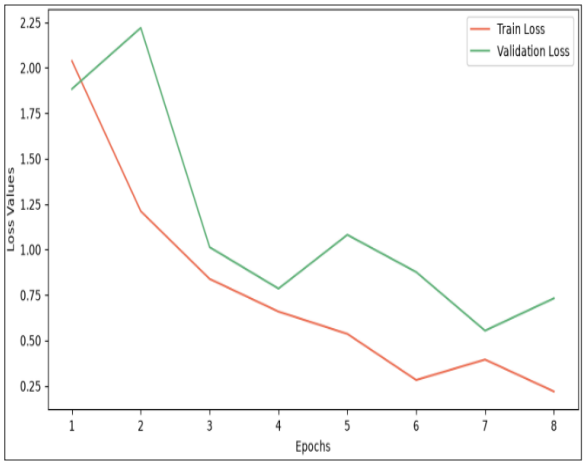

Figure 12. Plot of loss.

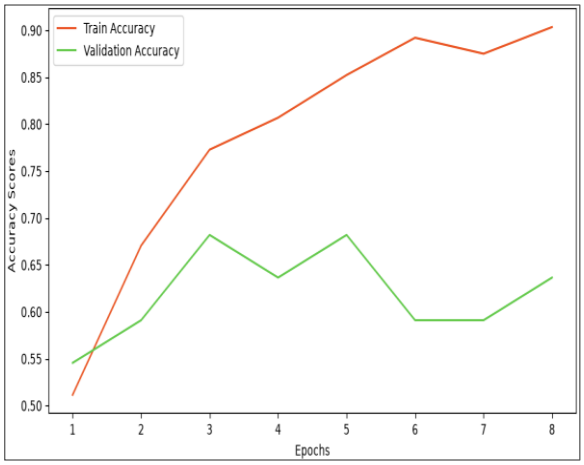

Figure 13. Plot of accuracy.

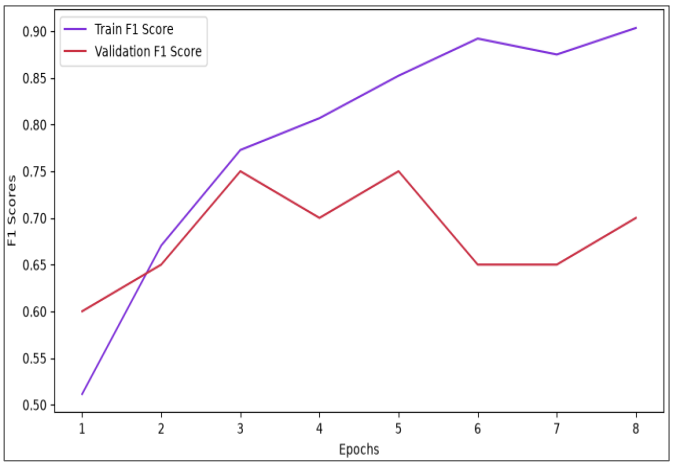

Figure 14. Plot of F1 score.

Table 7. Performance measures of classification as edible or not.

	Accuracy	**Precision**	**Recall**	**F1**
Boosting	0.6	0.547	0.6	0.542
Support vector machine classification	0.371	0.420	0.371	0.376
Neural network classification	0.657	0.782	0.657	0.567
K-nearest neighbors classification	0.514	0.432	0.514	0.513
Linear discriminant classification	0.657	0.657	0.657	0.657
Naïve Bayes classification	0.571	0.544	0.571	0.554
Decision tree classification	0.657	0.432	0.657	0.521
Random forest classification	0.600	0.603	0.600	0.593

This observation -that edible vs poisonous classification performs worse than medicinal vs non-medicinal classification on the same Korean wild-mushroom dataset, for both classical ML and deep learning–is consistent with how mushroom variation behaves in nature [9]. Moreover, medicinal status is often literature- and compound-based, whereas edible and poisonous status is more context-dependent and noisy, resulting in differences in classification performance. In addition, as shown in Figures 2 and 10, edible and poisonous species are more morphologically similar than are the medicinal and non-medicinal species.

5. Conclusion

Machine Learning Classification between medicinal and non-medicinal mushrooms using measurement datasets achieves the highest performance. Especially, LDA achieves an accuracy of around 94 percent.

However, Machine Learning Classification between edible and poisonous mushrooms achieved only 65 percent accuracy. One possible reason for this gap is that medicinal and non-medicinal mushroom species are more morphologically distinct than edible and poisonous species. Most of all, both medicinal and edible mushrooms are small in stem and spore size and are more common in winter and spring. Using deep learning models, both classifications achieved around 78 percent and 68 percent accuracy, respectively, indicating that a tabular measurement dataset can capture underlying ecological, morphological, biochemical, and pharmacological features more closely than pixel images, specifically for the classification between medicinal and non-medicinal. For the edible-versus-poisonous classification, deep learning slightly outperforms machine learning models. Moreover, both medicinal and edible mushrooms tend to appear more often during winter and spring seasons, while most mushroom species bloom during summer and fall. In addition, medicinal and edible mushrooms tend to be more saprotrophic.

Declarations

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Appendix

Table 8. ANOVA output table: Ecological type (0: Saprotrophic, 1: Mycorrhizal, 2: Parasitic).

Ecological	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	1.922	1	1.922	6.382	0.012	0.029
	Residuals	53.307	177	0.301			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	0.629	0.522	0.041	0.831	
	1 (medicinal)	20	0.300	0.733	0.164	2.442	

Table 9. ANOVA output table: Minimum spore length.

Spore length (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	49.768	1	49.768	3.649	0.058	0.015
	Residuals	2414.217	177	13.640			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	8.299	3.745	0.297	0.451	
	1 (medicinal)	20	6.625	3.232	0.723	0.488	

Table 10. ANOVA output table: Maximum spore length.

Spore length (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	99.943	1	99.943	4.210	0.042	0.018
	Residuals	4201.986	177	23.740			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	11.097	4.953	0.393	0.446	
	1 (medicinal)	20	8.725	4.144	0.927	0.475	

Table 11. ANOVA output table: Minimum spore width.

Spore width (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	90.559	1	90.559	17.540	< 0.001	0.085
	Residuals	913.855	177	5.163			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	5.443	2.304	0.183	0.423	
	1 (medicinal)	20	3.185	1.985	0.444	0.623	

Table 12. ANOVA output table: Maximum spore width.

Spore width (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	148.275	1	148.275	18.445	< 0.001	0.089
	Residuals	1422.848	177	8.039			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	7.039	2.903	0.230	0.412	
	1 (medicinal)	20	4.150	2.195	0.491	0.529	

Table 13. ANOVA output table: Minimum stem length.

Stem length (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	21630.982	1	21630.982	30.198	< 0.001	0.140
	Residuals	126787.242	177	716.312			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	40.044	27.959	2.217	0.698	
	1 (medicinal)	20	5.150	13.136	2.937	2.551	

Table 14. ANOVA output table: Maximum stem length.

Stem length (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	85874.833	1	85874.833	25.832	< 0.001	0.122
	Residuals	588410.284	177	3324.352			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	89.126	57.641	4.571	0.647	
	1 (medicinal)	20	19.600	57.793	12.923	2.949	

Table 15. ANOVA output table: Minimum stem thickness.

Stem thickness (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	847.614	1	847.614	13.508	< 0.001	0.065
	Residuals	11106.600	177	62.749			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	7.377	8.397	0.664	1.135	
	1 (medicinal)	20	0.470	1.272	0.284	2.706	

Table 16. ANOVA output table: Maximum stem thickness.

Stem thickness (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	4425.911	1	4425.911	12.547	< 0.001	0.061
	Residuals	62438.577	177	352.760			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	16.824	19.856	1.575	1.180	
	1 (medicinal)	20	1.040	2.782	0.622	2.675	

Table 17. ANOVA output table: Spring dummy variable.

Spring	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	0.579	1	0.579	4.895	0.028	0.021
	Residuals	20.930	177	0.118			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	0.119	0.325	0.028	2.723	
	1 (medicinal)	20	0.300	0.105	0.105	1.567	

Table 18. ANOVA output table: Winter dummy variable.

Winter	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Medicinal	0.367	1	0.367	18.326	< 0.001	0.088
	Residuals	3.544	177	0.020			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (non-medicinal)	159	0.006	0.079	0.006	12.610	
	1 (medicinal)	20	0.150	0.366	0.082	2.442	

Table 19. ANOVA output table: Ecological type (0: Saprotrophic; 1: Mycorrhizal; 2: Parasitic).

Ecological	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	2.879	1	2.879	9.734	0.002	0.047
	Residuals	52.350	177	0.296			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	0.743	0.440	0.051	0.592	
	1 (Edible)	105	0.486	0.606	0.059	1.248	

Table 20. ANOVA output table: Maximum spore length.

Spore length (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	73.654	1	73.654	3.083	0.081	0.012
	Residuals	4228.274	177	23.889			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	11.596	5.088	0.592	0.439	
	1 (Edible)	105	10.293	4.741	0.463	0.461	

Table 21. ANOVA output table: Minimum spore length.

Spore length (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	71.812	1	71.812	5.313	0.022	0.024
	Residuals	2392.174	177	13.515			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	8.866	4.202	0.489	0.474	
	1 (Edible)	105	7.580	3.257	0.318	0.430	

Table 22. ANOVA output table: Maximum spore width.

Spore width (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	135.530	1	135.530	16.710	< 0.001	0.081
	Residuals	1435.593	177	8.111			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	7.753	3.139	0.365	0.405	
	1 (Edible)	105	5.986	2.625	0.256	0.439	

Table 23. ANOVA output table: Minimum spore width.

Spore width (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	75.382	1	75.382	14.382	< 0.001	0.069
	Residuals	929.032	177	5.249			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	5.964	2.425	0.282	0.407	
	1 (Edible)	105	4.646	2.192	0.214	0.472	

Table 24. ANOVA output table: Maximum stem length.

Stem length (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	15097.696	1	15097.696	4.054	0.046	0.017
	Residuals	659187.421	177	3724.223			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	92.297	51.246	5.957	0.555	
	1 (Edible)	105	73.648	67.045	6.543	0.910	

Table 25. ANOVA output table: Minimum stem length.

Stem length (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	8439.245	1	8439.245	10.671	0.001	0.051
	Residuals	139978.978	177				
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	44.324	27.787	3.230	0.627	
	1 (Edible)	105	30.381	28.354	2.767	0.933	

Table 26. ANOVA output table: Maximum stem thickness.

Stem thickness (max)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	1446.004	1	1446.004	3.912	0.049	0.016
	Residuals	65418.484	177	369.596			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	18.446	24.336	2.829	1.319	
	1 (Edible)	105	12.674	14.605	1.425	1.152	

Table 27. ANOVA output table: Minimum stem thickness.

Stem thickness (min)	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	330.007	1	330.007	5.025	0.026	0.022
	Residuals	11624.208	177	65.673			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	8.223	10.372	1.206	1.261	
	1 (Edible)	105	5.466	6.021	0.588	1.102	

Table 28. ANOVA output table: Spring dummy variable.

Spring	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	0.925	1	0.925	7.951	0.005	0.037
	Residuals	20.584	177	0.116			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	0.054	0.228	0.026	4.212	
	1 (Edible)	105	0.200	0.402	0.039	2.010	

Table 29. ANOVA output table: Winter dummy variable.

Winter	**Cases**	**Sum of squares**	**df**	**Mean square**	**F**	**P**	ω^2
	Edible	0.063	1	0.063	2.898	0.090	0.010
	Residuals	3.848	177	0.022			
		N	**Mean**	**SD**	**SE**	**Coefficient of variation**	
	0 (Poisonous)	74	0.000	0.000	0.000	NaN	
	1 (Edible)	105	0.038	0.192	0.019	5.049	

Citation: Hyunmin Park, Jiwoo Chong, Hayoon Jung, Jaeyun Im and Bob Nam. 2026. Deep Learning and Machine Learning Comparison for Korean Wild Medicinal Mushrooms. International Journal of Recent Innovations in Academic Research, 10(3): 163-175.