Logistic Regression-Based Mushroom Classification System

VATSAL KATHIRIYA
INFORMATION TECHNOLOGY
L.D. COLLEGE OF ENGINEERING
AHMEDABAD,GUJARAT,INDIA-380015
22itkat044@ldce.ac.in

VARDAN PATEL
INFORMATION TECHNOLOGY
L.D. COLLEGE OF ENGINEERING
AHMEDABAD,GUJARAT,INDIA-380015
vardanp329@gmail.com

***Abstract*—This paper presents a machine learning approach for classifying mushrooms as edible or poisonous based on their physical characteristics. We developed a system using logistic regression that achieves 85% accuracy on a comprehensive mushroom dataset. The classification model leverages various visual and physical attributes of mushrooms, such as cap shape, gill color, and habitat. We implemented data preprocessing techniques to handle categorical features and employed visualization methods to understand feature importance. Our system provides a reliable baseline for mushroom classification with potential applications in food safety and mycological research. The web-based interface allows users to input mushroom characteristics and receive immediate classification results, making it accessible to both amateur mushroom hunters and professional mycologists.**

***Index Terms*—mushroom classification, logistic regression, categorical data, machine learning, food safety, feature visualization**

I. INTRODUCTION

Mushroom classification is a critical task in food safety, as consumption of poisonous mushrooms can lead to severe health issues including death. Traditional identification meth- ods rely on expert mycologists and visual inspection, which are both time-consuming and susceptible to human error. Machine learning approaches offer potential solutions by analyzing patterns in mushroom features that may not be immediately obvious to human observers.

In this paper, we present a machine learning system for classifying mushrooms as edible or poisonous based on their physical characteristics. Our system employs logistic regression, a fundamental classification algorithm that provides a good baseline for binary classification problems. While more complex models exist, logistic regression offers high interpretability, allowing us to understand which features most strongly indicate edibility or toxicity.

Our work focuses on:

Data preprocessing techniques for handling categorical mushroom features

Implementation of logistic regression for binary classification

Feature importance analysis to identify key determinants of mushroom toxicity

Development of a web-based classification interface for practical use

The resulting system demonstrates moderate accuracy with 85% correct classifications, providing a foundation for more sophisticated mushroom identification systems and contributing to safer mushroom foraging practices.

II. RELATED WORK

Several researchers have applied machine learning to mushroom classification problems. Wibowo et al. [1] compared various classifiers including Naïve Bayes, Decision Trees, and Neural Networks, achieving accuracies of 90-95%. Pinrattanasai [2] employed ensemble methods and achieved 97.2% accuracy using Random Forest.

Our work differs in that we focused on a simpler, more interpretable approach using logistic regression as a baseline model. While our accuracy is lower at 85%, the model provides clear insights into feature importance. Previous works have demonstrated that complex models like Random Forests and Neural Networks can achieve higher accuracy, but often at the cost of interpretability.

Recent advancements in the field include image-based classification systems that use convolutional neural networks to identify mushrooms from photographs [3]. These systems achieve comparable or better results than feature-based classification but require large datasets of mushroom images. Our approach retains the advantage of working with categorical descriptive features that can be easily input by users without requiring photography.

III. METHODOLOGY

A. Dataset Description

We utilized the Mushroom dataset from the UCI Machine Learning Repository [4], containing hypothetical mushroom samples with 22 categorical features such as cap shape, cap color, gill size, and odor. Each sample is labeled as either "edible" or "poisonous." The dataset presents several challenges including categorical attributes, missing values, and class imbalance.

The dataset contains:

- 61,096 mushroom instances
- 22 categorical features with 2 to 12 possible values each
- Two classes: edible (55.5%) and poisonous (44.5%)
- Various missing values, particularly in the ’stalk-root’ attribute

These features correspond to morphological characteristics of mushroom species, making the dataset appropriate for developing a classification system that relies on visually observable traits.

B. Data Preprocessing

Our preprocessing pipeline included the following steps:

1. **Handling Missing Values**: We identified missing values in attributes like ’stalk-root’ (2.48% of instances) and employed k-nearest neighbor imputation to estimate these values based on other features.

2. **Categorical Encoding**: We implemented one-hot encoding to transform categorical features into a format suitable for logistic regression. This expanded the feature space from 22 dimensions to over 100 binary features representing each possible category value.

3. **Feature Selection**: To reduce dimensionality and improve model performance, we applied statistical methods including chi-square tests to identify the most informative features for classification.

4. **Dataset Splitting**: The dataset was split into training (70%) and test (30%) sets using stratified sampling to maintain class distribution across both sets.

```
# Example code snippet for preprocessing
def preprocess_data(df, test_size=0.2, random_state=42):

    # Replace empty strings with NaN
    df = df.replace(”, np.nan)
    # Fill missing values with mode for categorical features
    for col in df.select_dtypes(include=[’object’]).columns:
        if df[col].isnull().sum() > 0:
            df[col] = df[col].fillna(df[col].mode()[0])
    # Extract target variable
    y = df[’class’].map({’e’: 0, ’p’: 1}) # edible: 0, poisonous: 1
    # Drop target from features
    X = df.drop(’class’, axis=1)
    # Split data
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=test_size, random_state=random_state, stratify=y
    )
    return X_train, X_test, y_train, y_test
```

C. Model Implementation

We implemented logistic regression as our classification algorithm using scikit-learn’s LogisticRegression class. Logistic regression is a statistical model that uses a logistic function to model a binary dependent variable, making it suitable for our binary classification task of edible versus poisonous mushrooms.

The model was implemented with the following hyperparameters:

- Regularization strength (C): 1.0
- Penalty: L2 (Ridge regression)
- Solver: liblinear
- Max iterations: 100

Hyperparameters were optimized using grid search with 5-fold cross-validation on the training set to find the best combination for our specific classification task.

(this takes lots of time to run on machine)

```
# Example code snippet for model training
def train_logistic_regression(X_train, y_train):
    # Create preprocessing pipeline with one-hot encoding
    preprocessor = ColumnTransformer(
        transformers=[
            (’cat’, OneHotEncoder(handle_unknown=’ignore’),
             X_train.select_dtypes(include=[’object’]).columns)
        ]
    )
    # Create pipeline with preprocessing and logistic regression
    pipeline = Pipeline([
        (’preprocessor’, preprocessor),
        (’classifier’, LogisticRegression(max_iter=100,
                                          C=1.0,
                                          solver=’liblinear’))
    ])
    # Train the model
    pipeline.fit(X_train, y_train)
    return pipeline
```

D. Visualization Methods

To better understand the data and model behavior, we implemented several visualization techniques:

1. **Class Distribution**: Visualizing the distribution of edible and poisonous mushrooms in the dataset to assess class balance.

2. **Feature Distribution**: Analyzing how different feature values are distributed across edible and poisonous classes to identify potential discriminative features.

3. **PCA Visualization**: Applying Principal Component Analysis to visualize high-dimensional data in 2D space and assess the separability of classes.

4. **Model Coefficients**: Visualizing the logistic regression coefficients to understand feature importance and their impact on classification decisions.

Correlation Heatmap: Examining correlations between numerical features to identify potential redundancies

IV. RESULTS AND DISCUSSION

A. Model Performance

Our logistic regression model achieved an accuracy of 85% on the test dataset. Table I presents the detailed performance metrics.

The detailed performance metrics.

(*Ref.* TABLE I)

The precision of 86.30% indicates that when our model predicts a mushroom is poisonous, it is correct about 86% of the time. The recall of 83.90% shows that the model correctly identifies about 84% of all poisonous mushrooms in the dataset. These results provide a reasonable baseline for mushroom classification, though there is room for improvement.

B. Feature Importance Analysis

By examining the coefficients of the logistic regression model, we identified the features most strongly associated with mushroom edibility or toxicity.

TABLE I
LOGISTIC REGRESSION PERFORMANCE METRICS

Metric	Value
Accuracy	85.00%
Precision	86.30%
Recall	83.90%
F1-Score	85.08%
AUC-ROC	0.929

The odor feature emerged as the most significant predictor, with foul, fishy, and pungent odors strongly indicating poisonous mushrooms, while almond and anise odors suggested edibility. Other important features included:

- **Gill color**: Brown and buff gills associated with edibility Spore print color:
- **Spore print color**: Green and white spore prints indicating toxicity
- **Ring type**: Absence of ring suggesting edibility
- **Cap color**: Purple caps associated with toxicity

This analysis provides practical insights for mushroom identification, aligning with mycological knowledge that odor is indeed a significant indicator of mushroom toxicity.

C. Limitations and Challenges

The relatively moderate accuracy of 85% suggests several potential limitations:

1. **Linear Decision Boundary**: Logistic regression creates a linear decision boundary, which may be insufficient for capturing complex relationships between mushroom features.
2. **Feature Interactions**: Important interactions between features might not be adequately captured by the model
3. **Data Quality**: Despite preprocessing efforts, issues such as class imbalance or noisy features may have impacted performance.
4. **Categorical Encoding**: The one-hot encoding of categorical features significantly expanded the feature space, potentially introducing sparsity issues.

These limitations suggest potential avenues for improvement in future work, particularly through the implementation of more complex models capable of capturing non-linear relationships

V. CONCLUSION AND FUTURE WORK

This paper presented a machine learning approach to mushroom classification using logistic regression, achieving 85% accuracy in distinguishing between edible and poisonous mushrooms. While not as high as more complex algorithms reported in the literature, this provides a valuable interpretable baseline and demonstrates the potential of machine learning in this domain.

Our feature importance analysis highlighted odor, gill color, and spore print color as key indicators of mushroom toxicity, aligning with mycological knowledge. The web-based interface we developed allows for practical application of the model, making it accessible to both amateur mushroom hunters and professional mycologists. Future work will focus on:

1. Implementing more sophisticated algorithms such as Random Forest, SVM, or deep learning approaches to improve classification accuracy
2. Enhancing feature engineering to better capture complex relationships between mushroom attributes
3. Expanding the dataset with additional samples and features
4. Incorporating image-based classification to complement feature-based classification
5. Developing a mobile application for field use with offline classification capabilities

Our work contributes to the application of machine learning in food safety and mycology, with practical implications for reducing the risk of mushroom poisoning through accessible classification tools.

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