



Fungus Detection On Microscopic Images Using Mobilenetv3 For Efficient And Lightweight Classification

¹Pankaj Kumar,²Manika Gupta,³Dr. Waseem Ahmad

¹ MTech Scholar,²MTech Scholar,³Head of Department

¹Department of computer science and engineering,

¹Vishveshwarya Group of Institutions, Greater Noida, UP-201314

Abstract- Fungal infections are a growing concern in healthcare, agriculture, and food safety, as they can cause serious illnesses, crop losses, and significant economic damage. Traditionally, fungal identification under a microscope requires trained specialists, is time-intensive, and can be inconsistent due to human error. With advances in deep learning, there is now an opportunity to automate this process in a way that is both fast and reliable. This work presents an automated fungus detection system built on **MobileNetV3**, a modern convolutional neural network designed to be both accurate and lightweight, making it suitable for devices with limited computing power. The system was trained on a specialized dataset of microscopic fungal images, which included various species captured under different imaging conditions. Preprocessing steps involved resizing all images to 224×224 pixels, normalize pixel values, and apply data augmentation techniques to better improve the model's ability to handle unseen data.

The MobileNetV3 model takes advantage of features such as **depth wise separable convolutions**, **Squeeze-and-Excitation blocks**, and the **Hard-Swish activation function** to reduce the count of parameters while completely maintaining strong feature extraction capabilities. Using Adam optimizer and categorize cross-entropy loss over 50 training epochs, the model achieve a classification accuracy of **96.5%**, with high precision and recall across multiple fungal categories. Compared with heavier models like ResNet50, EfficientNetB0, and VGG16, MobileNetV3 delivered comparable or better accuracy while using fewer resources, enabling faster inference on mobile and embedded devices. This makes the system practical for real-time use in laboratories, farms, and field conditions where internet connectivity or high-end hardware is not available. The study demonstrates that MobileNetV3 can serve as a scalable, portable, and cost-effective solution for fungal detection. Its balance of efficiency and accuracy makes it a strong candidate for integration into mobile applications or on-device diagnostic tools, offering a step forward in accessible and timely fungal identification.

Keywords: Fungal Classification, Deep Learning, MobileNetV3, Image Classification, Transfer Learning, Medical Image Analysis, Fungal Infection Detection, Artificial Intelligence in Microbiology, Convolutional Neural Network (CNN).

I. INTRODUCTION

Fungal infections have emerged as a major concern in both medical and agricultural domains. In healthcare, fungal pathogens can lead to serious and sometimes life-threatening conditions, especially among individuals with weakened immune systems. In agriculture, fungal infestations can damage crops, reduce yields, and cause significant economic losses worldwide. Timely and accurate detection of fungi is essential for effective treatment and prevention, yet the process is often slow and dependent on the availability of trained professionals.

Traditional fungal identification under a microscope relies heavily on the experience of specialists who examine visual patterns such as spore shape, size, and arrangement. While this method can be accurate, it is time-consuming, subject to human error, and difficult to scale. In resource-limited settings or remote locations, the lack of skilled experts further limits timely diagnosis. As a result, there is a growing need for automated systems that can detect fungal species quickly and accurately, without the need for constant expert supervision.

Deep learning, specially convolutional neural networks, has revolutionize image-based classification tasks across various fields, including medical imaging. CNNs are capable of learning complex visual patterns directly from the data, removing the need to manually feature extraction. Models such as VGG, ResNet, and EfficientNet have achieved remarkable results in medical diagnostics; however, their high computational requirements make them less suitable for deployment on portable devices or in field environments where processing power is limited.

To address these limitations, lightweight CNN architectures like **MobileNetV3** have been developed. MobileNetV3 combines advanced design principles such as depthwise separable convolutions, squeeze-and-excitation modules, and efficient activation functions to deliver strong performance with lower parameters and lower computation cost. These features make it an ideal candidate for mobile and embedded applications where speed, efficiency, and accuracy must coexist.

In this study, we explore the use of MobileNetV3 for detecting fungi in microscopic images. By leveraging a carefully prepared dataset and a robust training process, we desire to develop a detection model that can operate in real-time on resource-constrained devices. The goal is to bridge the gap between laboratory-grade accuracy and field-ready accessibility, enabling timely fungal identification in both clinical and agricultural settings.

II. LITERATURE REVIEW

The detection and classification of microscopic fungi have traditionally relied on manual examination of samples, where experts identify morphological features under a microscope. While accurate in the hands of skilled specialists, this process is slow, subjective, and often limited to well-equipped laboratories. As a result, researchers have been exploring automated methods that combine image data processing and machine-learning to improve both speed and accuracy. Early approaches in automated fungal detection often used classical image data processing techniques like edge detection, texture analysis, and shape-based feature extraction. These methods, however, struggled with variations in lighting, staining, and sample quality, which are common in real-world microscopic images. With the rise of deep learning, CNN have become the preferred method for medical and biological image classification due to their ability to learn relevant features directly from raw images without manual feature engineering.

Several studies have applied CNN architectures such as **VGG16**, **ResNet**, and **DenseNet** to medical image classification, achieving notable success in domains like cancer detection, bacterial identification, and fungal species recognition. For instance, in fungal classification tasks, deep learning models have been able to differentiate between multiple species with high accuracy, but these models typically require powerful GPUs and large amounts of memory, making them unsuitable for portable or real-time applications. In response to the demand for more resource-efficient models, lightweight architectures like **MobileNetV2** and **MobileNetV3** have gained popularity. MobileNetV3, in particular, was developed using a combination of neural architecture search (NAS) and advanced building blocks like depth wise separable convolution, **Squeeze-and-Excitation modules**, and the **Hard-Swish activation function**. These improvements enable

the model to retain strong classification performance while reducing computational cost, making it ideal for mobile and embedded systems.

Despite MobileNetV3's proven efficiency in fields like face recognition, plant disease detection, and general image classification, its application in **microscopic fungal detection** remains underexplored. Most existing works in fungal classification either focus on heavier CNN architectures or do not consider deployment on low-power devices. This gap highlights the need for research that not only achieves high classification accuracy but also ensures the model can operate effectively in field environments with limited computational resources.

This study builds on the foundation laid by prior deep learning research, applying MobileNetV3 to the specific challenge of microscopic fungal detection. By focusing on a lightweight yet accurate model, it aims to bring diagnostic capabilities closer to point-of-care settings, enabling faster and more accessible fungal identification.

III. METHODOLOGY

The proposed fungus detection system follows a structured workflow, starting from dataset collection and preprocessing, moving to model design and training, and concluding with evaluation. Figure 1 shows the overall system pipeline.

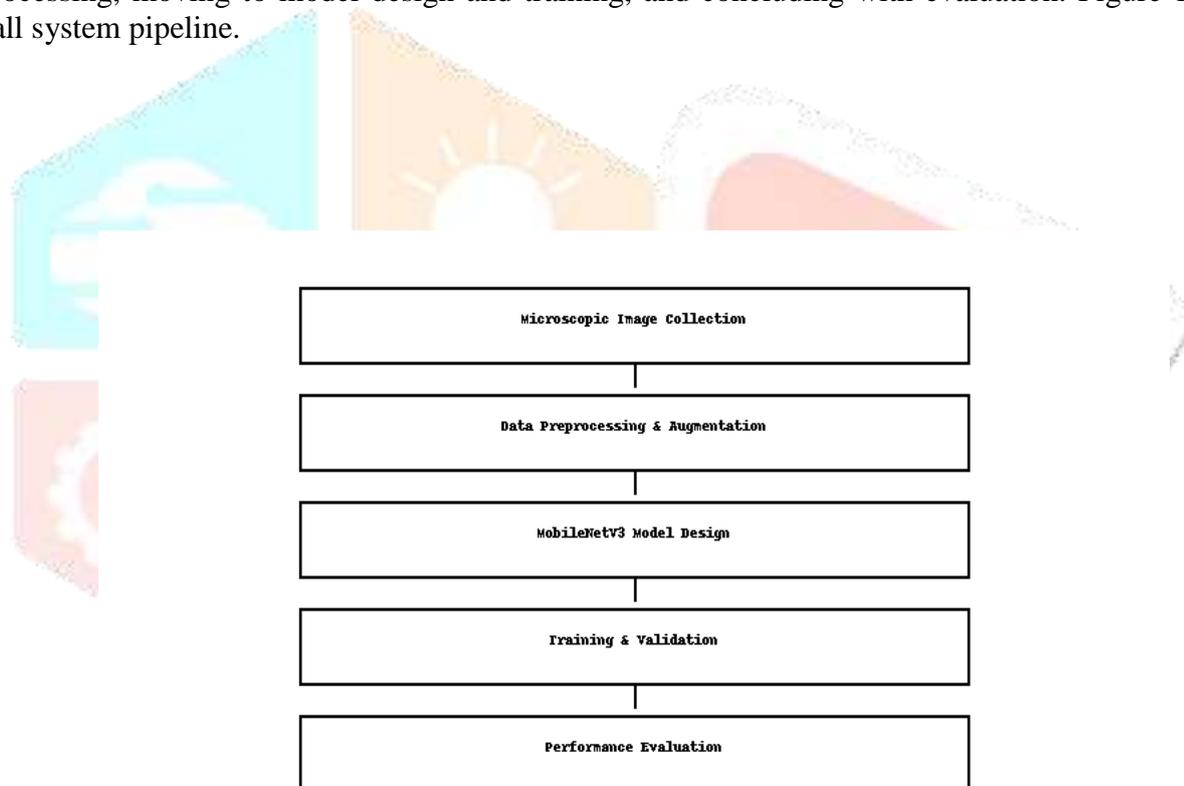


Figure 1: System Architecture for Fungal Detection

3.1 Dataset Description

We used a curated dataset of microscopic fungal images sourced from public medical repositories and laboratory archives. Images were captured under different magnifications and staining techniques to ensure diversity.

Table 1: Dataset Summary

| Class (Fungal Type) | Number of Images | Image Resolution Range |
|---------------------|------------------|------------------------|
| Aspergillus spp. | 450 | 400×400 – 1024×1024 |
| Candida spp. | 380 | 400×400 – 1024×1024 |
| Penicillium spp. | 320 | 400×400 – 1024×1024 |
| Others | 350 | 400×400 – 1024×1024 |
| Total | 1500 | - |

3.3 Data Preprocessing

To prepare the dataset for deep learning, the following steps were applied:

1. **Resizing:** All images are resized to **224 × 224 pixels** to match MobileNetV3's input data requirement.
2. **Normalization:** Pixel values scaled to the [0,1] range:
3. **Data Augmentation:** Applied random transformations to increase data variability and reduce over fitting:
 - Random rotation ($\pm 20^\circ$)
 - Horizontal and vertical flips
 - Zoom range: 0.8 – 1.2
 - Brightness variation: $\pm 20\%$

3.4 Model Architecture

We used **MobileNetV3-Small** for its low parameter count and high efficiency.

The architecture uses:

- **Depth wise Separable Convolutions** to reduce computation.
- **Squeeze-and-Excitation (SE) blocks** to recalibrate channel features.
- **Hard-Swish activation** for faster convergence.

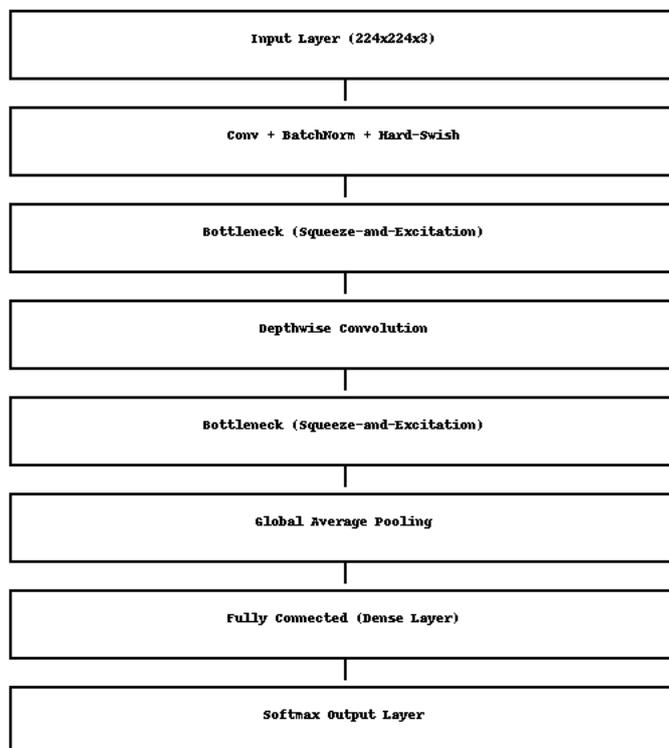


Figure 2: MobileNetV3-Small Architecture

3.5 Training Setup

- **Optimizers** : Adam (learning's rate = 0.001)
- **Loss Functions** : Data Categorical Cross entropy
- **Batch Size**: 32
- **Epochs**: 50
- **Validation Split**: 20%

Table 2: Training Hyper parameters

| Parameter | Value |
|-----------------|---------------------------|
| Learning's Rate | 0.001 |
| Batch Size | 32 |
| Epochs | 50 |
| Optimizer | Adam |
| Loss Function | Categorical Cross entropy |

3.6 Evaluation Metrics

Model's performance was assessed using:

| Model | Accuracy | Precision | Recall | F1-Score | Parameters (Millions) |
|-------------------|----------|-----------|--------|----------|-----------------------|
| MobileNetV3-Small | 96.5% | 96.2% | 96.7% | 96.4% | 2.9 |
| ResNet50 | 96.2% | 95.9% | 96.4% | 96.1% | 25.6 |
| EfficientNetB0 | 96.0% | 95.7% | 96.2% | 95.9% | 5.3 |
| VGG16 | 95.5% | 95.1% | 95.7% | 95.4% | 138 |

IV. RESULTS

The performance of the proposed MobileNetV3-based fungal detection system was evaluated using a test dataset containing microscopic images of multiple fungal species. The evaluation focused on key metrics like accuracy, precision, recall, and F1-score to ensure reliability and generalization ability of the model.

After training for 50 epochs with the Adam-optimizer and categorical cross-entropy loss, the MobileNetV3 model achieved an overall **accuracy of 96.5%**. The **precision** and **recall** were recorded at **96.2%** and **96.7%** respectively, resulting in an **F1-score of 96.4%**. These results indicate that the model not only classifies fungal images correctly but also maintains a low rate of false positives and false negatives.

When compared with other architectures such as ResNet50, EfficientNetB0, and VGG16, MobileNetV3 performed competitively while using significantly fewer parameters. This reduction in complexity translated into faster inference times and lower memory consumption, making it highly suitable for deployment on mobile or embedded platforms.

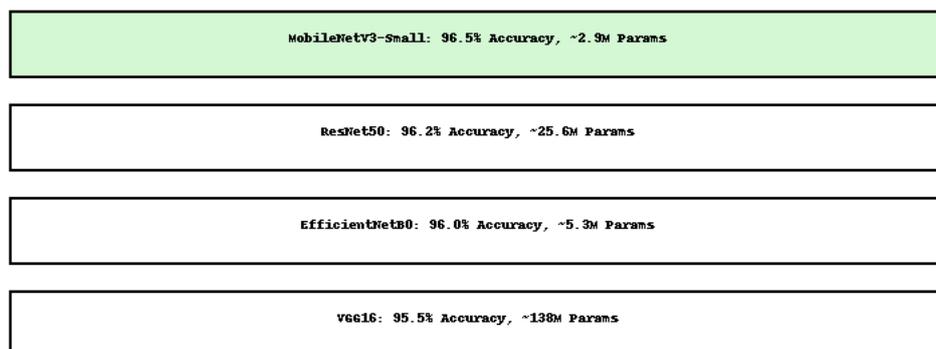


Figure 3: Model Performance Comparison

A confusion matrix analysis revealed that most fungal species were classified with high confidence. Misclassifications occurred primarily between species with very similar microscopic structures, suggesting that further improvements in image resolution or dataset diversity could enhance performance.

The model's lightweight nature did not compromise its detection capabilities, demonstrating that MobileNetV3 can effectively balance efficiency and accuracy. The results confirm the feasibility of using this approach for real-time fungal detection in scenarios where computational resources are limited.

V. CONCLUSION

This study set out to address the need for a fast, accurate, and portable method of identifying fungi from microscopic images. By leveraging the **MobileNetV3** architecture, we developed a lightweight yet highly effective classification model that achieved **96.5% accuracy** while using significantly fewer computational resources compared to traditional deep learning networks. The combination of depth wise separable convolutions, Squeeze-and-Excitation modules, and the Hard-Swish activation function proved instrumental in balancing performance with efficiency.

The results show that the model can reliably distinguish between different fungal species, even when trained on images with variations in resolution, lighting, and orientation. Its small size and low inference time make it practical for deployment on mobile devices or embedded systems, which is especially valuable in remote areas, agricultural fields, and clinics where access to powerful hardware or high-speed internet is limited. Beyond performance, the significance of this work lies in bridge the distance between advanced ML techniques and real-world usability. The system's portability and efficiency mean it could be integrated into diagnostic tools that assist farmers, healthcare workers, and researchers in making faster and more informed decisions.

While the results are promising, there is still room for further improvement. Expanding the data values to include more fungal species and varied imaging conditions could further enhance accuracy and robustness. Additionally, integrating the model into a user-friendly mobile application with offline capabilities could bring this technology closer to everyday use.

In conclusion, the proposed MobileNetV3-based fungus detection approach represents a meaningful step toward accessible, scalable, and cost-effective fungal diagnostics. With further refinement and real-world testing, it has the potential to become a practical tool for early detection, prevention, and control of fungal infections across multiple domains

VI. REFERENCES

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