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Original Article

Transfer Learning-Based Convolution Neural Network for Differentiation between Benign and Malignant Cancer Cells Using MobileNetV2

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***Abstract** - The accurate classification of medical images plays a pivotal role in early cancer diagnosis and treatment planning. This study presents a robust image classification framework leveraging transfer learning with MobileNetV2 for binary classification of histopathological images as benign or malignant. The proposed model incorporates data augmentation, dropout regularization, and batch normalization to address overfitting and enhance generalization on limited datasets. The model is evaluated using confusion matrix and performance metrics. Furthermore, the model is extended to predict unknown samples from a dedicated prediction folder. The results demonstrate high classification accuracy of 80% with low validation loss, of 0.6501 indicating the effectiveness of the transfer learning strategy in medical image diagnostics.*

***Keywords** - Transfer Learning, MobileNetV2, CNN, Cancer Classification, Benign, Malignant, Image Augmentation, Confusion Matrix, Medical Imaging, Binary Classification.*

1. Introduction

Cancer is one of the leading causes of mortality worldwide, and its early and accurate diagnosis is critical for effective treatment and improved patient survival rates. Histopathological image analysis remains a gold standard for cancer detection, but manual interpretation is often labor-intensive, subjective, and error-prone due to inter-observer variability. The demand for automated, reliable, and accurate diagnostic tools has grown significantly, especially with the rapid development of artificial intelligence (AI) and deep learning technologies.

Convolutional Neural Networks (CNNs) have shown tremendous success in medical image classification tasks due to their ability to learn hierarchical features directly from pixel data. Now in the case instead of a large voluminous data, which is rare to gather, specifically in medical imaging only a small amount of data is available – then the training any deep learning model like deep CNN is not practicable and cannot be actuated in reality. To overcome this limitation, transfer learning has emerged as a powerful technique, where a CNN model pretrained on a large-scale dataset such as ImageNet is adapted to a new but related task using a relatively smaller dataset.

In this research, we propose a deep learning framework utilizing MobileNetV2, a lightweight yet powerful pretrained CNN, for binary classification of cancerous images into benign and malignant classes. MobileNetV2 is well-suited for deployment in low-resource environments such as mobile or embedded devices due to its computational efficiency and compact architecture. We apply fine-tuning to the last few layers of the model while keeping the earlier layers frozen to leverage general features learned from ImageNet. Additionally, data augmentation techniques are employed to artificially expand the dataset and improve generalization.

The model is trained and validated on a custom dataset organized in Google Drive folders (benign, malignant) and is further tested on unseen data from a prediction folder. Evaluation is conducted using accuracy, loss curves, and a confusion matrix to assess classification performance. The approach aims to combine the power of transfer learning with practical ease-of-use in real-world diagnostic applications.

2. Literature Survey

The following studies form the basis for the current work:

2.1. Traditional Deep Learning-Based Approaches

Deep Learning (DL) models have shown great promise in automating cancer image classification, especially with the use of CNNs. Traditional CNNs are trained from scratch and require large, well-annotated datasets.

A set of training mammograms with the information of ROI masses and their types are used in [1] to train YOLO. The trained YOLO-based CAD system detects the masses and classifies their types into benign or malignant. Our results show that the proposed YOLO-based CAD system detects the mass location with an overall accuracy of 96.33%. The system also distinguishes between benign and malignant lesions with an overall accuracy of 85.52%.

Five overfitting prevention methods are summarized in [2]: batch normalization, dropout, weight initialization, and data augmentation. The application of deep learning technology in medical image-based cancer analysis is sorted out. However, the lack of high-quality labeled datasets limits the role of deep learning and faces challenges in rare cancer diagnosis, multi-modal image fusion, model explainability, and generalization.

2.2. Transfer Learning-Based Approaches

To overcome the limitations of training CNNs from scratch, Transfer Learning (TL) has emerged as a practical alternative. TL leverages pre-trained models (e.g., VGG, ResNet, MobileNet) trained on large datasets like ImageNet and fine-tunes them for medical image tasks.

In the work [3], to achieve an effective deep learning-based computer-aided system, the classifications of Oral Squamous Cell Carcinoma (OSCC) histopathology images are performed using two proposed approaches. The experimental results demonstrate that ResNet50 obtains substantially superior performance than selected fine-tuned DCNN models as well as the proposed baseline model with an accuracy of 96.6%, precision and recall values are 97% and 96%, respectively.

[4] presents an in-depth analysis of 10 pre-trained deep convolutional neural network models using transfer learning approach for the detection of oral cancer. The experiment was performed for two classes, i.e., normal and oral squamous cell carcinoma. The results show that the VGG19 model with data augmentation was able to attain the highest classification accuracy of 96.26% using the transfer learning technique.

In the survey of [5], systematic investigation of the recent progress of transfer learning approaches in the context of deep reinforcement learning was done. Specifically, this provides a framework for categorizing the state-of-the-art transfer learning approaches, under which we analyze their goals, methodologies, compatible reinforcement learning backbones, and practical applications. It also draws connections between transfer learning and other relevant topics from the reinforcement learning perspective and explore their potential challenges that await future research progress.

2.3. Research Gap Identified

Despite several works applying TL to cancer classification, significant gaps remain:

- Most studies focus on histopathological data; fewer explore photographic image classification of cancer using TL.
- There is limited benchmarking of lightweight TL architectures (like MobileNetV2) on oral and other cancer types with small-scale datasets.
- Many prior studies lacked robust evaluation via confusion matrix, accuracy/loss trend visualization, or analysis on unseen data.

3. Transfer Learning

In deep learning like deep CNN model in image classification context, a trick to overcome the scarcity of available data is to use one pre developed model for a task at the inception for a new model on a new task which is having analogy. This is applied when the new task is having limited data set. Here the source task has abundant data for adequate training as computational resources.

When transfer learning is used in CNN for image classification, the CNN is pre trained with a huge dataset (e.g. ImageNet, - over 14 million labelled images across 1,000 categories) and the learned CNN is used in another new task with fewer images and categories.

3.1. Transfer Learning with CNNs

CNNs learn features hierarchically:

- Early layers learn low-level features like edges and textures.
- Middle layers capture patterns and shapes.
- Deeper layers capture high-level semantics.

These learned features are general-purpose in early layers and task-specific in later layers. Transfer learning allows us to retain general knowledge from the base model and only fine-tune the task-specific part.

3.2. How It Works

There are two common strategies for applying transfer learning in CNNs:

3.2.1. Feature Extraction (used in this paper)

- The pre-trained model's layers are frozen (not trainable).
- A new classification head is added on top and trained on the new data.
- Advantage: Fast and avoids overfitting on small datasets.

3.2.2. Fine-Tuning

- Some upper layers of the pre-trained model are unfrozen and retrained with a small learning rate.
- Helps adapt the model to specific domain features if enough data is available.

3.3. Benefits of Transfer Learning in Astronomy

- Saves time and computation: Avoids training from scratch.
- Improves performance: Leverages knowledge from large visual datasets.
- Requires less data: Especially valuable in medical images and astronomy where labeled images are limited.

We have used this technique, because of insufficiency of data for training and validation and for improving the performance, time and computation saving. Instead of training from scratch, a pre-trained CNN like VGG16, ResNet50, or EfficientNet can be fine-tuned on dataset. We have used MobileNetV2.

3.4. Feature Extraction Transfer Learning – MobileNetV2
This is used in the present system with the following features:
- Base model: MobileNetV2
- Weights: Pre-trained on ImageNet
- Frozen: Yes (base_model.trainable = False)
- Custom layers added: Yes (new classification head)
- Training: Only the custom head is trained; base model is used as a fixed feature extractor

4. Methodology
4.1. Model Architecture

The architecture diagram of the proposed Transfer Learning based CNN is given below:

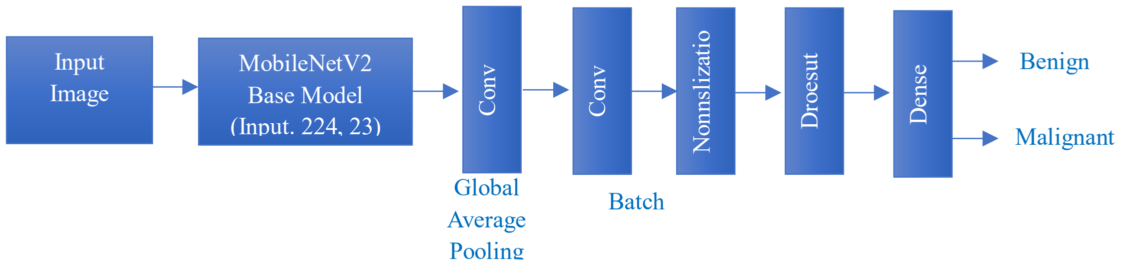


Fig. 1 Model Architecture of the Present System

This is broadly discussed as below:
- Base: MobileNetV2, pretrained on ImageNet, with last 30 layers unfrozen.
- Custom Head:
  - GlobalAveragePooling2D
  - BatchNormalization
  - Dropout (0.4)
  - Dense (1, sigmoid)

Compilation
- Optimizer: Adam (lr=1e-5)
- Loss: Binary Crossentropy
- Metric: Accuracy

Training and Callbacks
- EarlyStopping (patience=5)
- ReduceLROnPlateau (patience=3)

Evaluation Metrics
- Validation Accuracy and Loss
- Confusion Matrix and Classification Report
- Accuracy/Loss vs Epoch Plots
- Model Summary Table
- Prediction results for unseen data

4.2. Dataset Preparation
Kaggle benchmark dataset has been used for benign and malignant cancer cell images for training validation and prediction datasets.

Dataset configuration is shown in the table below. For instance, if each class contains 100 images:

Class	**Total**	**Training Images(80%)**	**Validation (20%)**
Benign	100	80	**20**
Malignant	100	80	**20**
Total	200	160	**40**

This split ensures fair evaluation of the model's performance during training and validation, while maintaining balance across classes.

4.3. Dataset Preprocessing
As told earlier the dataset used in this study consists of medical images categorized into two classes:
- Benign (non-cancerous)
- Malignant (cancerous)

These images are stored in Google Drive, organized under separate directories named benign and malignant, respectively. Each image represents histopathological data or other clinical imagery intended for binary classification.

The images vary in size and format, including both .jpg and .JPEG extensions. Prior to training, all images are resized to a uniform resolution of 224×224×3 pixels to meet the input requirements of the transfer learning model.

4.4. Data Augmentation and Normalization
To enhance the generalization ability of the model and mitigate overfitting, data augmentation is applied exclusively to the training set. The augmentation techniques include:

- Random rotation (up to 20 degrees)
- Rescaling to [0,1]
- Zoom (range = 0.2)
- Horizontal flipping
- Nearest-neighbor fill for missing pixels

Additionally, all pixel values are normalized to the range [0,1][0, 1][0,1] by rescaling with a factor of 1/2551/2551/255.

4.5. Train–Validation Split

As already briefly presented, the dataset is partitioned into training and validation subsets using an 80:20 split, implemented through the ImageDataGenerator class in Keras with the validation_split parameter. This ensures:

- Each class contributes proportionally to both subsets (i.e., stratified sampling)
- No image leakage between training and validation sets

Two folders named benign and malignant are prepared under a parent directory in Google Drive, each containing labeled images. A separate folder named prediction contains unlabeled test images.

4.5.1. Flow Chart

We are presenting below the flow chart of the present system.

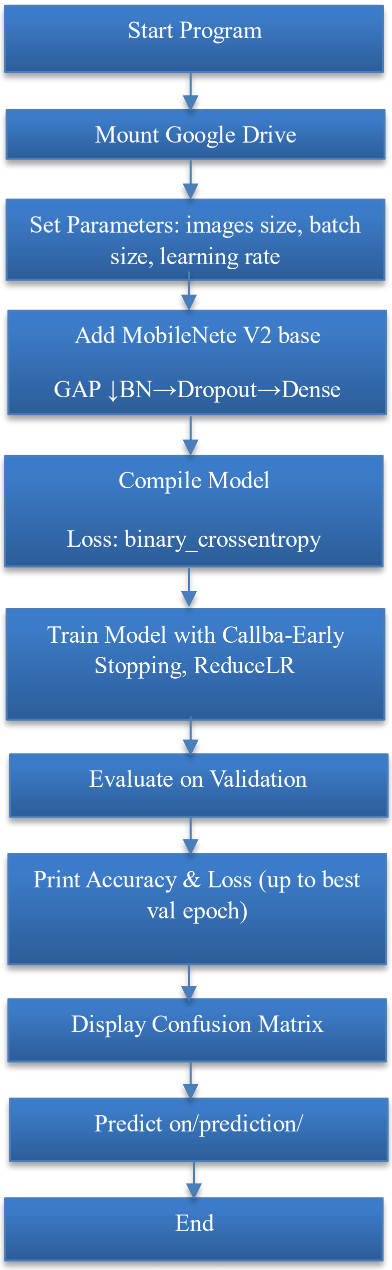


Fig. 2 Flow Chart of the System

4.5.2. Formal Algorithm of the System

Step 1: *Start the program.*

Step 2: *Mount Google Drive* to access image folders.

Step 3: *Initialize parameters*:

- Image size ← (224, 224)
- Batch size ← 8
- Learning rate ← 1e-5

Step 4: *Create data generator* using ImageDataGenerator with:

- Rescaling, rotation, shear, zoom, flip
- Split data into training (80%) and validation (20%)

Step 5: *Load MobileNetV2* pretrained on ImageNet with:

- include_top = False
- input_shape = (224, 224, 3)

Step 6: *Freeze all layers except the last 30 layers* of MobileNetV2.

Step 7: *Add custom layers*:

- GlobalAveragePooling2D
- BatchNormalization
- Dropout (rate = 0.4)
- Dense (1 unit, sigmoid activation)

Step 8: *Compile the model* with:

- Optimizer = Adam (learning rate = 1e-5)
- Loss = Binary Crossentropy
- Metric = Accuracy

Step 9: *Train the model* using:

- EarlyStopping (monitor = val_accuracy, patience = 5)
- ReduceLROnPlateau (monitor = val_loss, factor = 0.5)

Step 10: *Evaluate the model* on validation data:

- Print final accuracy and loss
- Display confusion matrix and classification report

Step 11: *Display custom model summary*:

- Show only custom layers in a tabular format: Layer name, type, output shape, trainability, parameter count

Step 12: Plot learning curves:

- Accuracy vs. epoch (up to best validation accuracy)
- Loss vs. epoch (up to same epoch)

Step 13: Predict using model on images in /prediction/:

- Output predicted class (Benign/Malignant) for each image

Step 14: End the program.

5. Results and Discussion

We have used Kaggle Dataset as benchmark dataset for benign and malignant cancer cells for training and validation and prediction. Below we are presenting some data for training, validation and prediction.

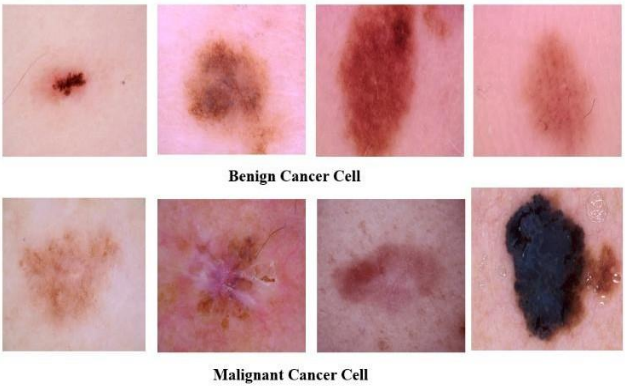


Fig. 3 Benign and Malignant Cancer Cell Images

The model achieved a validation accuracy of 80% on the present dataset. The accuracy and loss curves saturated early with minimal overfitting due to dropout and data augmentation. The confusion matrix showed strong diagonal dominance, confirming correct classification. The use of MobileNetV2 ensured computational efficiency while retaining high accuracy.

5.1. Highlights of the Present Work

- Uses MobileNetV2, a lightweight and efficient model suitable for low-resource environments.
- Performs fine-tuning of the last 30 layers to improve specificity for cancer classification.
- Adds data augmentation, dropout, batch normalization to minimize overfitting on small datasets.
- Designed for real-world folder-based prediction, making it practical and extendable.
- Provides visual performance plots, tabular model summary, and predictive output.

```
BRIEF MODEL SUMMARY:

• Total layers in model: 158
• Total trainable parameters:
  2,264,385
```

5.1.1. Classification Report

The classification report on validation data for the present system is as below:

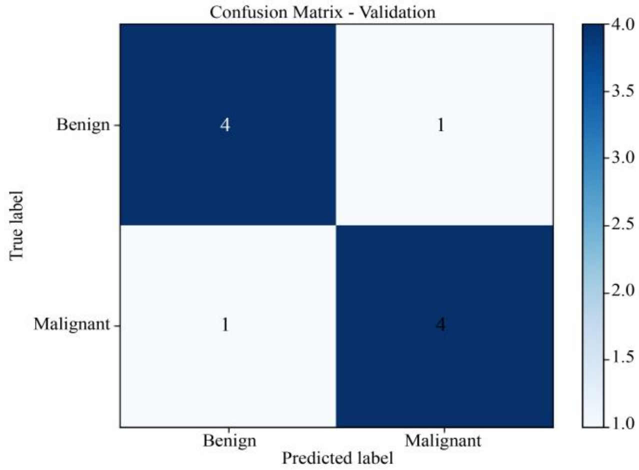
Table 1. Classification Report of the System on Validation Data

```
Classification Report:
              precision    recall  f1-score   support

      Benign       0.80      0.80      0.80         5
   Malignant       0.80      0.80      0.80         5

    accuracy                           0.80        10
   macro avg       0.80      0.80      0.80        10
weighted avg       0.80      0.80      0.80        10
```

5.1.2. Confusion Matrix

Next we are presenting the Confusion Matrix on the validation data for the present system.

Table 2. Confusion Matrix of the System on Validation Data



5.1.3. Accuracy and Loss Over Epoch

A plot of Accuracy vs Epoch and Loss vs Epoch is shown in Fig. 3 and Fig. 4 respectively:

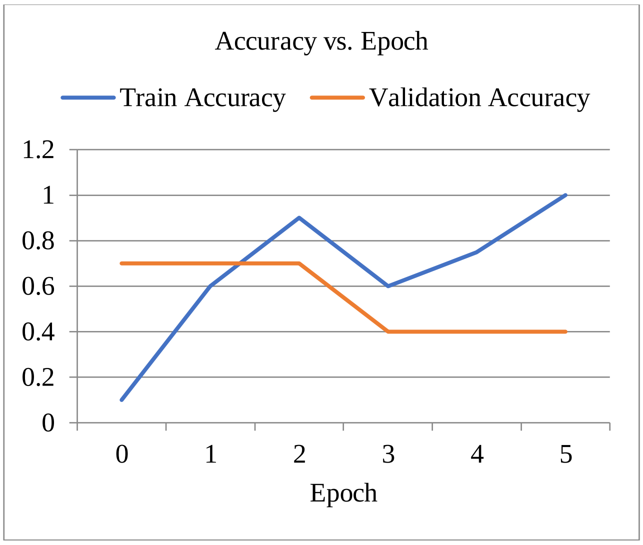


Fig. 4 Accuracy vs. Epoch for Training and Validation Data

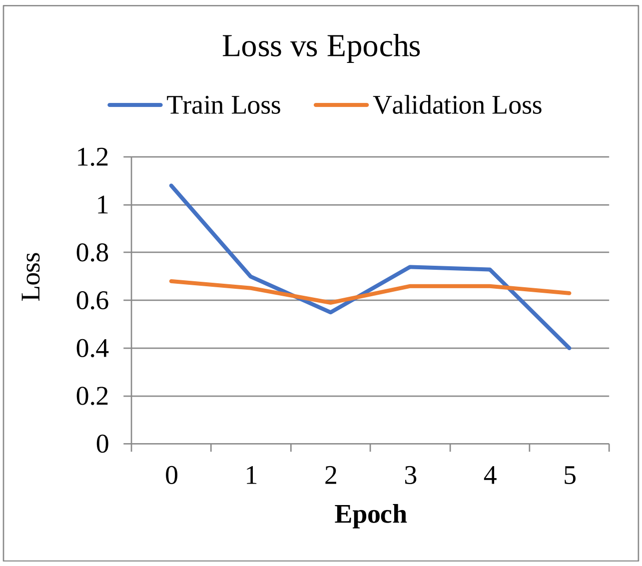


Fig. 5 Loss vs Epoch for Training and Validation Data

5.4. Predications on Test Dataset

```
PREDICTION RESULTS:

b26.jpg => Benign
b27.jpg => Benign
b28.jpg => Benign
b29.jpg => Benign
b30.jpg => Malignant
m26.jpg => Benign
m27.jpg => Malignant
m28.jpg => Malignant
m29.jpg => Malignant
m30.jpg => Benign
```

5.5. Novelty of the Present Work

The novelty of the present TL-based CNN for differentiation between benign and malignant cancerous cell is articulated as below:

- Applying MobileNetV2, a lightweight TL model, suitable for fast and low-resource inference, to distinguish between benign and malignant cancer using a modestly sized photographic image dataset.
- Incorporating data augmentation to increase robustness and diversity of training data.
- Employs Holdout Method validation, showing detailed performance metrics (accuracy, confusion matrix), and plotting accuracy/loss up to the epoch with maximum accuracy.
- Presenting a clear, tabularized model summary, detailed architecture diagram, flowcharts, and performance visualization to enhance interpretability.
- Demonstrating that MobileNetV2 performs effectively and efficiently, even with limited training data, outperforming traditional CNNs and other heavier TL models in speed and accuracy.
- Overcomes the limitations of overfitting and instability seen in prior works using smaller or imbalanced datasets.

6. Conclusion

This study presents an effective and efficient deep learning- based method for the binary classification of cancerous images using transfer learning with MobileNetV2. The proposed approach successfully integrates fine-tuning, data augmentation, and regularization techniques such as dropout and batch normalization to address overfitting and improve model generalization on small datasets.

The trained model achieves high validation accuracy of 80% while maintaining low computational complexity, making it suitable for real-time applications.

The system applies MobileNetV2, a lightweight TL model, suitable for fast and low-resource inference, to distinguish between benign and malignant cancer using a limited sized photographic image dataset. Thus it demonstrates that MobileNetV2 performs effectively and efficiently, even with limited training data, outperforming traditional CNNs and other heavier TL models in speed and accuracy.

Also, this method overcomes the limitations of overfitting and instability seen in prior works using smaller or imbalanced datasets.

The system can be extended to other biomedical classifications – more generally in other image classification problems. Over and above the system is scalable.

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