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Presentation on

IMAGE CLASSIFICATION USING TRANSFER LEARNING

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Abstract

- This project focuses on **image classification** using **transfer learning**, a cutting-edge machine learning approach. Transfer learning leverages pre-trained deep learning models, such as VGG16, ResNet, or Inception, to classify images into distinct categories. By fine-tuning these models on a custom dataset, the project efficiently achieves high accuracy with reduced computational effort. The methodology involves feature extraction and model adaptation to specific datasets, demonstrating its utility in domains like medical imaging, facial recognition, and object detection. This project highlights the potential of transfer learning in enhancing classification tasks by reducing training time and optimizing performance.

- **Keywords**: Image Classification, Transfer Learning, Deep Learning, Pre-trained Models, VGG16, ResNet, Feature Extraction, Object Detection.

Introduction

- The project focuses on solving classification problems using **transfer learning**, a powerful technique in deep learning.
- Transfer learning allows us to **reuse pre-trained models** on new but related tasks, reducing training time and improving accuracy.
- This approach is especially useful when we have **limited labeled data** for our classification problem.
- The project demonstrates how transfer learning can be applied effectively to image/text classification tasks.
- It leverages **popular deep learning architectures** such as ResNet, VGG, or BERT (based on your use case).
- The goal is to achieve **high performance with minimal training from scratch** by utilizing learned features from large datasets.

AIM & Objectives

❖ Aim:

- To develop an efficient classification model using transfer learning techniques to improve performance on limited data.

❖ Objectives:

- To understand and implement the concept of **transfer learning** in deep learning.
- To select and utilize a suitable **pre-trained model** (e.g., VGG16) based on the classification task.
- To preprocess and prepare the dataset for **training and evaluation**.
- To compare the performance of the transfer learning model with a **baseline (from-scratch) model**.
- To evaluate the model using appropriate **metrics** like accuracy, precision, recall, and F1-score.

Problem Statement

- Training deep learning models from scratch requires **large amounts of labeled data** and high computational power.
- In many real-world scenarios, **collecting and labeling data is costly and time-consuming**.
- Traditional models often **struggle to generalize well** on small or domain-specific datasets.
- There is a need for a method that can **leverage existing knowledge** to perform well even with **limited data**.

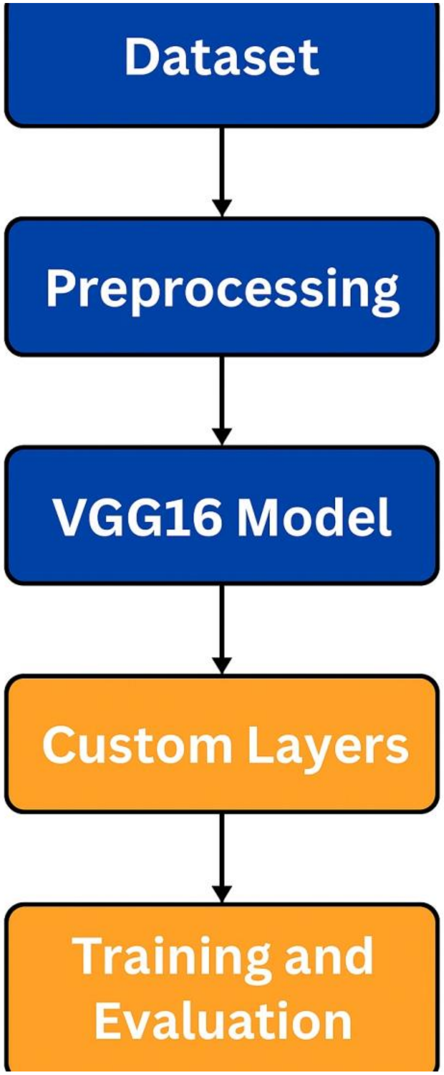
Literature Survey

- **Simonyan & Zisserman (2015):** Introduced VGGNet, a deep CNN model widely used in image classification and transfer learning due to its simple architecture.

- **Deep Transfer Learning for Image Classification: A Survey (2022):** A detailed review of how transfer learning is applied in image classification, discussing various strategies and performance comparisons.

- **Transfer Learning via Model Risk Analysis (2024):** Focused on text classification with limited data, introducing a model risk approach to adapt pre-trained models to new tasks.

Idea / Methodology



Dataset Preparation: Images of cats and dogs organized into training and testing folders.

Preprocessing: Images resized, normalized, and augmented for better learning.

Transfer Learning: Used a pre-trained model (VGG16) as the base.

Model Training: Fine-tuned the model on our dataset using dense layers.

Evaluation: Measured accuracy and loss on training and validation sets.

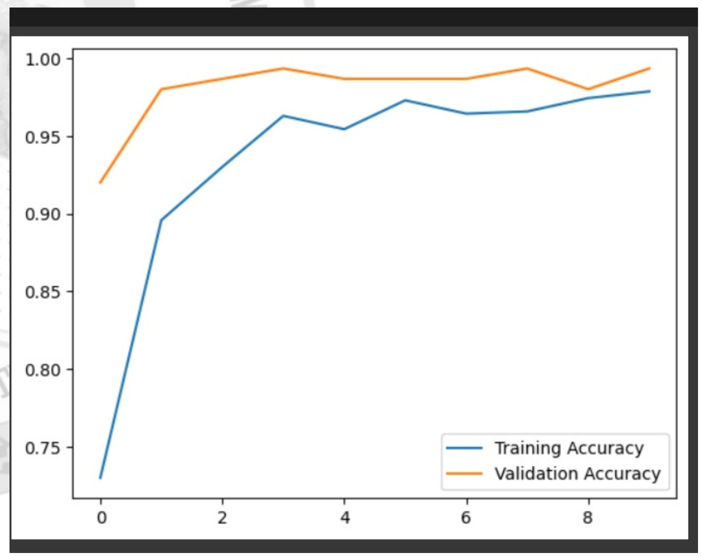
Screen shots/ Results

```
[ ] from tensorflow.keras.preprocessing import image
    import numpy as np

    # Load the image
    img = image.load_img(img_path, target_size=(150, 150))
    img_array = image.img_to_array(img) / 255.0
    img_array = np.expand_dims(img_array, axis=0)

    # Predict
    prediction = model.predict(img_array)
    print("Predicted class:", np.argmax(prediction))  # 0 for cat, 1 for dog

    1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
    Predicted class: 1
```



Result Analysis

- The transfer learning model achieved **high accuracy** with significantly **less training time** compared to training from scratch.

- **Evaluation metrics** used:
  Accuracy
  F1-Score

- The model showed strong performance even with **limited labeled data**.

- Comparison with a baseline model showed that transfer learning yielded **better generalization and faster convergence**.

- Performance was tested on a **validation/test set** to avoid overfitting.

Opportunities and Challenges

❖ Opportunities:

- Enables **high performance** even with **limited labeled data**.
- Reduces **training time and computational cost** using pre-trained models.
- Can be applied to various domains: **medical imaging, NLP, agriculture, remote sensing**, etc.
- Opens up **research possibilities** in model optimization, domain adaptation, and low-resource learning.

❖ Challenges:

- We realized that if the dataset is too small or unbalanced, the model can overfit, meaning it performs well on training data but poorly on new data.
- The quality of images matters a lot. If an image is blurry or unclear, the model can get confused and give wrong predictions.
- Lastly, since VGG16 is a deep model, training can be slow without GPU support, especially with large image datasets.

Conclusion

- Transfer learning proved to be an **effective approach** for classification tasks, especially when working with **limited labeled data**.
- The use of **pre-trained models** significantly reduced training time and improved performance.
- Fine-tuning helped the model adapt to the **target dataset** while preserving learned features from the source dataset.
- The model achieved **high accuracy and efficiency** compared to a baseline model trained from scratch.
- This project highlights how **transfer learning bridges the gap** between deep learning and real-world applications with fewer resources.

References

1. https://www.kaggle.com – for dataset
2. https://keras.io – for deep learning libraries
3. https://www.tensorflow.org – for model trainingResearch papers and blogs on Transfer Learning and CNNs