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A NOVEL DEEP LEARNING AND TRANSFER LEARNING-BASED SYSTEM FOR FRUIT RECOGNITION AND CLASSIFICATION

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ABSTRACT
This paper looks into how to use advanced Convolutional Neural Networks (CNNs) for automated fruit classification. It focuses on models like Inception-V3, VGG-19, MobileNet, ResNet-50, and a standard CNN. This study utilized a dataset obtained from Kaggle, comprising photos of five fruit categories: Apples, Bananas, Grapes, Mangoes, and Strawberries. We carefully chose the architecture for each model because it could extract complex visual cues and accurately classify them, even when the fruit looked, felt, or smelled different. The models were trained and tested as part of the evaluation process to see how well they worked for real-world categorization tasks. The models were evaluated on their generalization abilities and computing efficiency by using convolutional layers, residual connections, and efficient network topologies. This research elucidates the benefits and drawbacks of various CNN architectures, aiding in the advancement of automated systems for fruit recognition. These kinds of technologies can be used in quality control for farms, managing inventory in stores, and automated sorting procedures. They are big steps forward in automating the food business.

Keywords:
Fruit Classification, Convolutional Neural Networks (CNN), Deep Learning, Inception-V3, VGG-19, MobileNet, ResNet-50, Image Classification, Feature Extraction, Agricultural Automation

INTRODUCTION
Artificial intelligence is becoming a big part of everyday life, and the food and farming industries are not far behind. Artificial intelligence has been utilized in various domains, including healthcare, education, agriculture, and numerous other fields. AI has been used in healthcare to find several diseases, such as skin cancer, to find different body parts, to guess which children will have neurodevelopmental abnormalities, to help with mental health, and to help with other problems [1]. The globe is confronting problems in agriculture, like a growing population, global warming, and other environmental dangers created by people. These problems could lead to a higher need for food supplies. AI and the computer-vision-driven business seem to be able to help by speeding up the procedures of harvesting, quality control, picking and packing, sorting, grading, and more. Fruits are highly fragile and go bad rapidly. About 30–35% of the fruits that are picked go to waste because unskilled workers don't know how to properly identify, classify, and grade them. When it comes to buying and selling fruit, sorting it into categories is seen to be the hardest and most important step. Someone who sells or buys fruits has to know about the different kinds of fruits so they can price them correctly. So, someone needs to know a lot about how to tell the difference between different kinds of fruits.
Fruit classification is very important for figuring out the overall quality, shelf life, and nutritional content of fruits. Correct classification helps customers figure out what kind and quality of fruit they want to buy, which helps them make the right pricing selections. It also helps shoppers figure out how much the fruits they buy are

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worth. Also, fruit classification is very important for producers and merchants since it helps them keep track of their stock and makes sure that their products fulfil quality standards. Figure 1: Sample Fruit Images Used for Classification.

Figure 1: Sample Fruit Images Used for Classification

Numerous methodologies for the identification, categorization, and grading of fruits, vegetables, and seeds have been established distinct ways to group fruits into distinct classifications have been suggested. For example, Altaheri et al. [2] put out a robotic harvesting approach intended to categorize five distinct varieties of date fruits. This model was right around 99% of the time. This model trained and tested itself on a dataset that it made itself. There was a total of 8000 photos in the collection. Shamim Hossain et al. [3] created a model for classifying fruits for use in industry in another study. They trained and tested their model with a dataset that was open to the public. One of the datasets had pictures of fruits that are hard to tell apart. The suggested model got 85% right. Gulzar et al. [4] put forth a model for classifying seeds using VGG16. The model was 99% accurate with thirteen different types of seeds. Hamid et al. [5], on the other hand, suggested a model that employed the same dataset and MobileNetV2 as the basis model. They used a transfer learning method, and the model got 94% correct. Saranya et al. [6] conducted a comparative study in which they trained various machine learning and deep learning models on a public dataset. This dataset has pictures of many kinds of fruit, like apples, bananas, oranges, and pomegranates. They determined that models based on deep learning are better than those based on machine learning. Rojas-Aranda et al. [7] created a deep learning model to sort fruits in supermarkets. The goal of this study was to make the checkout experience in retailers better. When the fruits were in plastic bags, the model was 95% accurate. When the fruits were not in plastic bags, the model was only 93% accurate. Sridhar et al. [8] put forward a model for 31 distinct kinds of fruits utilizing a mix of different methods. They used CNN and an autoencoder to work with the vast amounts of data from 31 different fruits. They say that their model was 99% accurate. Zhou et al. [9] created a model to find out how plump the strawberries are. They were able to find strawberries in the greenhouse with about 86% accuracy. They used RGD data to train the model they suggested. Mamat et al. [10] put forward a model utilizing deep learning in conjunction with Only Look Once (YOLO) versions and implemented transfer learning for palm oil fruit. The model achieved 98.7% accuracy for palm oil fruit. Some researchers concentrated on the identification and categorization of fruit illnesses. The VGG19 architecture was chosen as the basic model for this study. They said that their model was about 99% accurate at sorting fruits and their illnesses. Assuncao et al. [11] proposed a deep learning model for mobile devices in a different study. This model's goal is to sort peaches by how fresh they are and to find three sorts of diseases that can affect peach produce. The model's accuracy was noted to be 96%. They used certain preprocessing methods to make the proposed model more accurate. Some researchers have looked at the quality of the fruits, including. Garillos-Manliguez et al. [12] put forward a methodology for figuring out how ripe papaya fruit is. This model is different from others because it is trained on photos taken in both visible and hyperspectral light. These pictures depict not only the outside of the fruit, but also the inside. The program was able to guess how ripe papaya fruit was with 97% accuracy. Herman et al. [13] selected oil palm fruit to assess its maturity. There were about seven different stages of maturity in the oil palm fruit in the dataset they used. They trained two well-known architectures, AlexNet and DenseNet, on this dataset. They found that DenseNet was 8% more accurate than AlexNet. Mahmood et al. [14] conducted a comparative analysis of two prominent architectures (AlexNet and VGG16) to assess the maturity level of jujube fruit. There were three different types of photos in the dataset, based on how ripe they were (unripe, ripe, and overripe). They also did some

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preprocessing, including data augmentation. They said that VGG16 was better than AlexNet since it got 98% accuracy.
The apple is a fruit from the Rosaceae family that hails from Asia. More than 63 countries grow it, and China is the biggest producer. Apples are thought to be the healthiest food since they have a lot of water, carbohydrates, organic acids, vitamins, minerals, and dietary fibers. There are many different kinds of apples, which is the fourth most grown and eaten fruit in the world. There are about 7500 types of apples in the globe. Different types of apples are good for your health in different ways. It is not easy for most people to tell the difference between all the many kinds of apples and other fruits. So, we need a deep learning-based strategy or model that can tell different sorts of fruits apart and get rid of the need for an expert. This would make it easier and more accurate to identify and classify different types of fruits.

This work proposes a deep learning methodology for the categorization and identification of various fruit types. The suggested model uses a transfer learning method to cope with problems that come up when there isn't enough training data. This method promotes the concept of avoiding training the model from the beginning, which greatly shortens the time it takes to train the model. This work utilized the established deep learning model, Transfer leaning, as the foundational model, which was further enhanced by incorporating five additional layers to increase accuracy and decrease the error rate in the classification process. The suggested model is trained on a dataset of 40 different kinds of fruit. The results demonstrate that the suggested model was the best at correctly identifying different kinds of fruits

OBJECTIVES

This research investigates the utilization of sophisticated Convolutional Neural Network (CNN) architectures for the automation of fruit classification. It talks about common deep learning models like Inception-V3, VGG-19, MobileNet, ResNet-50, and a regular CNN. For training and testing, we use a dataset from Kaggle that has five types of fruit: apples, bananas, grapes, mangoes, and strawberries. These models were chosen because they are very good at picking up complicated visual elements from pictures.
Each architecture is carefully built to manage changes in how fruit looks, such as changes in color, texture, size, and form. The models use important parts of deep learning, like convolutional layers to get features, residual connections to make learning better, and lightweight structures to make calculations faster. These traits let the models do strong categorization even when things are hard in the real world.
The evaluation process involves training and testing each model to analyze its classification performance. To see how well they work, people look to things like accuracy, generalization ability, and computing efficiency. A comparative analysis is done to find out what each CNN architecture does well and what it doesn't do well, which helps us understand how well they work in different situations.

The findings of this study advance the creation of intelligent and automated fruit recognition systems. These kinds of systems can be used in quality control for farming, managing retail inventory, and automated sorting procedures. The study shows that deep learning techniques could help the food industry become more automated and work more efficiently.

METHODOLOGY

The proposed classification framework is structured to ensure accurate identification of eight distinct fruit types. The process begins with image acquisition, where high-quality images of fruits are captured under varying conditions to create a diverse dataset. Next, image preprocessing techniques such as resizing, normalization, and noise reduction are applied to enhance data quality. The dataset is then divided into training, testing, and validation sets to train and evaluate the models effectively. To address the challenges of data scarcity and class imbalance, data augmentation methods including rotation, flipping, and color adjustments are employed, increasing the model's robustness and generalization capability.

The core of the classification system is built using advanced Convolutional Neural Networks (CNNs), specifically Inception-V3, VGG-19, MobileNet, and ResNet-50. These models are selected for their proven performance in image recognition tasks. Each model undergoes rigorous training and evaluation using metrics such as accuracy, precision, recall, and F1-score to ensure optimal performance. Upon achieving satisfactory results, a user-friendly, web-based application is developed to provide real-time fruit recognition. This application serves both individual users, assisting in personal fruit identification, and industrial sectors, offering scalable solutions for automated fruit sorting and quality control.

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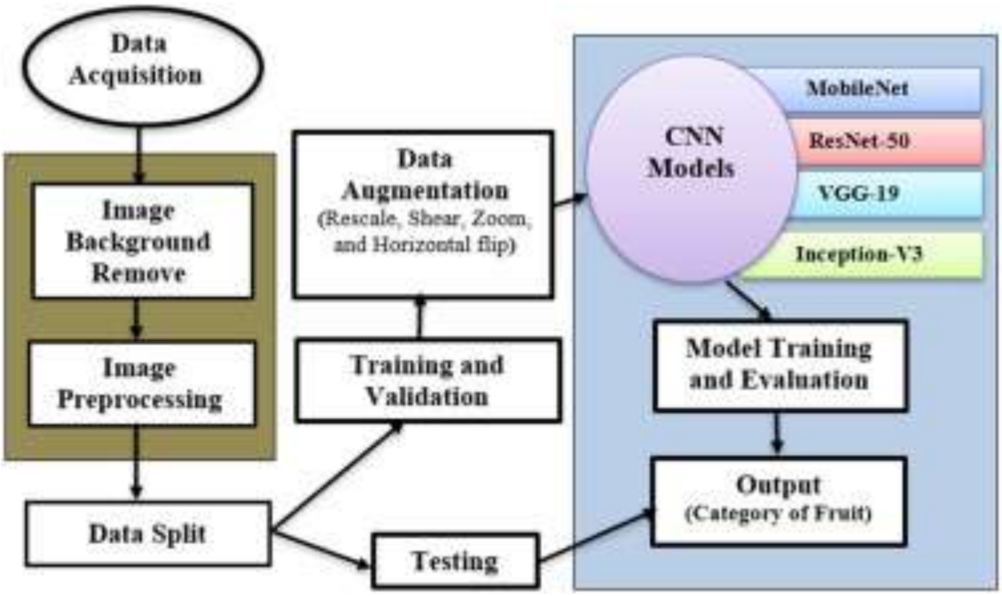

Figure 2. Proposed methodology to classify fruits.

Dataset used in experimental results:

The fruit classification dataset, sourced from Kaggle, consists of images of five distinct fruit types: Apples, Bananas, Grapes, Mangoes, and Strawberries. Each fruit class contains 2,000 images, resulting in a comprehensive dataset of 10,000 images. These images exhibit variations in shape, size, and color, captured under diverse lighting conditions. The dataset is specifically designed to support the training and testing of computer vision models for various tasks, including object detection, image classification, and segmentation. Its balanced distribution and visual diversity make it an excellent resource for developing robust and accurate models.

Researchers and developers can utilize this dataset for a range of applications, such as testing new image classification algorithms and benchmarking existing ones. Additionally, it serves as a valuable resource for machine learning model training in practical scenarios, particularly within the agricultural industry for tasks like fruit grading and sorting. By using this dataset, advancements in image analysis and classification technologies can be achieved, contributing to the broader field of computer vision and its applications in real-world environments. 1 depicts the quantity of training, testing, and validation data of fruit.

Table 1. Quantity of training and testing data.

Fruit Name	Training	Testing
Apples	940	20
Bananas	940	20
Grapes	940	20
Mangoes	940	20
Strawberries	940	20

Image preprocessing and augmentation

Before feeding the data into the identification model, several preprocessing steps and techniques are applied to ensure optimal performance. The dataset consists of high-resolution PNG images with three RGB channels, each with an 8-bit resolution. One of the primary preprocessing steps involves background removal to eliminate unnecessary features, enhancing the clarity of the fruit images. To standardize the input size for the model, the images are resized to 224 × 224 pixels using a deep learning-based resizing method. This ensures uniformity across the dataset, reducing computational complexity while maintaining essential visual information.

After preprocessing, the images are converted into NumPy arrays, which accelerates the training process by facilitating efficient data manipulation and matrix operations. The entire dataset is then systematically divided into three distinct subsets: training, testing, and validation. For model training, 60% of the data is used, while the remaining 40% is equally distributed between testing and validation. This balanced

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split helps in monitoring the model's performance and ensures that it generalizes well to unseen data. The preprocessing pipeline plays a crucial role in preparing the dataset for accurate and reliable fruit classification.

Neural networks

Machine learning models like MobileNet, VGG-19, Inception-v3, and ResNet-50 are applied for image augmentation and feature extraction. The methodology and working process of all convolutional neural network models are explained below.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a specialized type of deep learning model designed for processing grid-like data, such as images. They are inspired by the structure and functioning of the animal visual cortex, allowing them to automatically and adaptively learn spatial hierarchies of features, from simple edges and textures to more complex patterns. CNNs consist of three primary types of layers: convolution, pooling, and fully connected layers. The convolution and pooling layers are responsible for extracting features from the input data, while the fully connected layer uses these features to generate the final output, typically for classification or recognition tasks. By applying small grids of parameters known as kernels across image pixels, CNNs efficiently identify relevant patterns and features, regardless of their position within the image.

The convolution layer is the core component of CNNs, performing a series of mathematical operations that capture spatial features from input images. Each layer extracts increasingly abstract features as data passes through multiple convolution and pooling layers, leading to a hierarchical understanding of the image content. The extracted features are then fed into the fully connected layer for final classification. The optimization of kernel parameters during training is achieved using algorithms like backpropagation and gradient descent, minimizing the error between predictions and actual labels. This adaptive learning process makes CNNs highly effective for image recognition, object detection, and various other computer vision tasks.

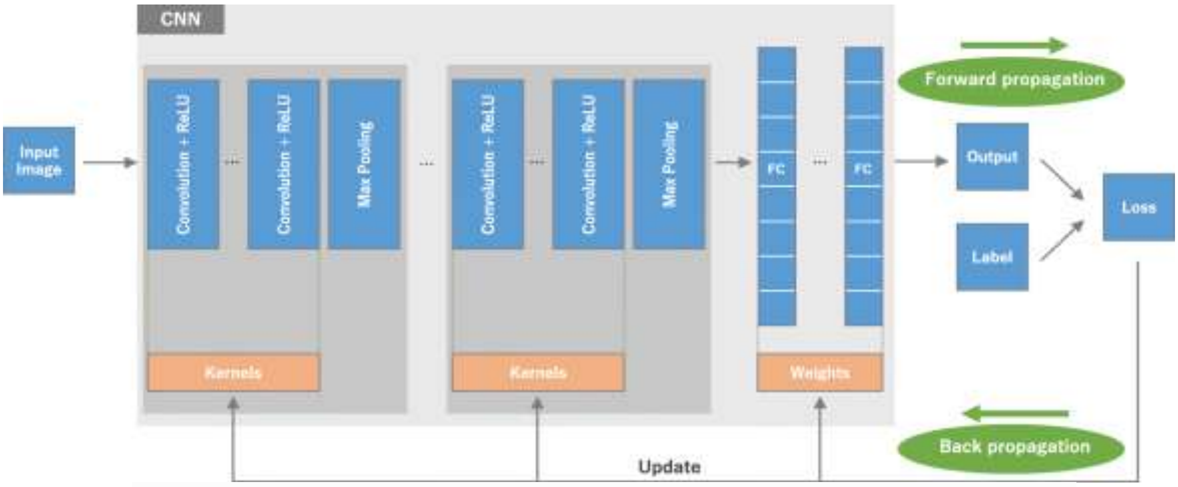

Figure 3: Convolutional neural network (CNN) architecture and the training process

The proposed Convolutional Neural Network (CNN) model is implemented using a sequential architecture, consisting of three convolutional blocks followed by classification layers. The first convolutional block applies a 2D convolutional layer with 32 filters, a 3x3 kernel size, and ReLU activation. Padding is set to 'same' to ensure the output maintains its dimensions, and a max pooling layer with a pool size of 2x2 is used to reduce spatial dimensions and computational complexity. Similarly, the second block uses 64 filters, applying convolution and max pooling layers with the same configurations. The third block reverts to 32 filters, maintaining a consistent feature extraction process while further refining the features.

Following the convolutional blocks, the model includes a flattening layer to convert the multidimensional feature maps into a 1D vector for classification. The classification segment consists of two dense (fully connected) layers with 64 and 32 neurons, both using ReLU activation for non-linearity. To prevent overfitting, dropout layers are incorporated with a dropout rate of 20%, randomly disabling a fraction of neurons during training. The final output layer contains 5 neurons with a softmax activation function, representing the five fruit classes. This architecture ensures an efficient and effective classification of fruit images, balancing feature extraction and generalization.

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MobileNetV2:

This subsection presents the proposed model for fruit classification using the TL-MobileNetV2 architecture, which is derived from MobileNetV2.MobileNetV2 is specifically designed for mobile and resource-constrained environments, offering significant advantages in terms of reduced memory usage, lower computational costs, and enhanced compatibility with mobile applications.

Originally, MobileNetV2's classification layer contains approximately one thousand nodes. However, to tailor it for the fruit classification task, the number of nodes in the classification layer was adjusted. To further enhance accuracy, a customized head consisting of five distinct layers was integrated into the base MobileNetV2 model, replacing the original classification layer.

3 VGG19:

The VGG19 architecture, a well-known convolutional neural network (CNN) originally developed for image classification tasks. VGG19 is a variant of the VGG network, containing 19 layers, including convolutional and fully connected layers. The code utilizes TensorFlow and Keras to create a custom model based on VGG19 by modifying its top layers for a specific classification task. The function build_VGG19_model takes two parameters: input_shape, which defines the dimensions of the input images, and num_classes, representing the number of output categories in the classification task.

The function initializes a pre-trained VGG19 model with weights from ImageNet while excluding the top fully connected layers. Instead of using the default classifier, the model's output is flattened using the Flatten () layer. A fully connected Dense layer with 256 neurons and ReLU activation is then added, followed by a Dropout layer with a rate of 0.2 to reduce overfitting. The final output layer is a dense layer with num_classes neurons and a softmax activation function, making the model suitable for multi-class classification.

Once the new classifier layers are added, the function constructs the final model using the Model class, specifying the input as base_model. input and the output as the predictions layer. An important step in transfer learning is freezing the layers of the pre-trained model to retain its learned features. This is accomplished using a loop that sets layer. trainable= False for all layers in base_model. This ensures that during training, only the newly added layers are updated, while the original VGG19 layers remain unchanged.

The model is then compiled using the Adam optimizer, which is widely used in deep learning due to its adaptive learning rate capabilities. The loss function is set to categorical_crossentropy, which is suitable for multi-class classification problems. Additionally, the metric for evaluation is set to accuracy, allowing the model's performance to be measured in terms of correct predictions. After defining the function, the code calls build_VGG19_model with specific input dimensions (128, 128, 3), indicating that the model expects RGB images of size 128x128 pixels.

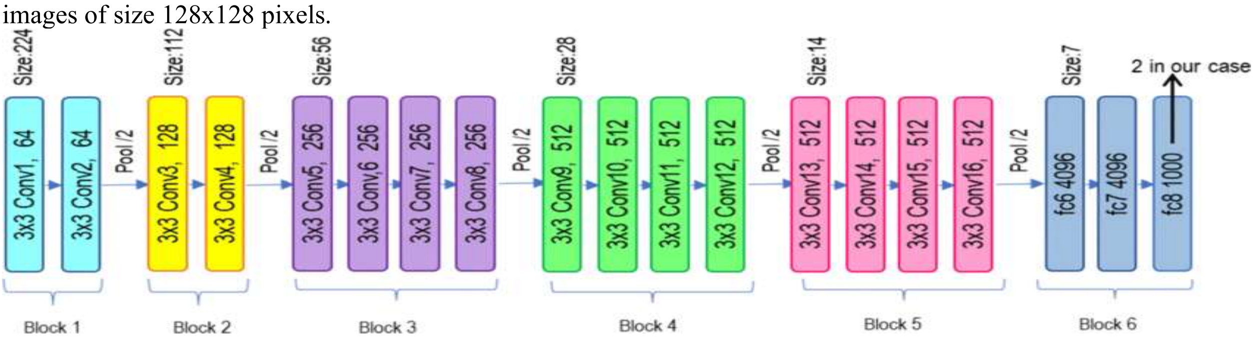

Figure 4: VGG19 Architecture

InceptionV3:

InceptionV3 is a state-of-the-art convolutional neural network (CNN) architecture that was developed by Google as an improvement over its predecessor, InceptionV2. It was introduced as part of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) and has shown exceptional performance in image classification tasks. InceptionV3 is characterized by its unique design, which employs a combination of convolutional filters of varying sizes to capture both fine and coarse visual features. This architecture significantly reduces computational complexity while maintaining high accuracy.

A key innovation in InceptionV3 is the use of factorized convolutions. Instead of applying large convolutional filters, the network uses smaller, more efficient filters by factorizing convolutions into multiple stages. For example, a 3x3 convolution can be replaced by two 1x3 and 3x1 convolutions, reducing the number of parameters and computational cost. Additionally, asymmetric convolutions are implemented to further enhance efficiency and capture diverse features.

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InceptionV3 includes auxiliary classifiers to mitigate the vanishing gradient problem. These classifiers are applied to intermediate layers of the network and provide additional gradients to improve convergence during training. The use of label smoothing is another significant enhancement, which prevents the model from becoming too confident in its predictions, thereby reducing overfitting and improving generalization.

To maintain computational efficiency, InceptionV3 employs efficient grid size reduction techniques using strided convolutions instead of traditional pooling layers. This ensures the preservation of essential features while reducing the spatial dimensions of feature maps. By doing so, the network maintains high-quality feature representations with fewer computations.

InceptionV3 has demonstrated exceptional performance in a variety of applications, including medical imaging, autonomous driving, and satellite image analysis. Its ability to capture intricate details makes it particularly suitable for complex visual recognition tasks. Additionally, due to its pre-trained availability on large datasets like ImageNet, InceptionV3 serves as a reliable backbone for transfer learning in numerous specialized applications.

ResNet-50:

ResNet-50 is a convolutional neural network (CNN) that significantly advanced deep learning applications. Introduced in 2015 by Kaiming He and his team at Microsoft Research Asia, ResNet stands for Residual Network, named after the residual blocks that define its architecture. Built on a deep residual learning framework, ResNet-50 enables the training of extremely deep networks, comprising hundreds of layers, without the degradation in performance often seen in traditional networks.

Before ResNet, researchers observed a counterintuitive phenomenon — adding more layers to a neural network didn't always improve results. In theory, a deeper network should learn more complex representations, but in practice, it often suffered from vanishing gradients and poor accuracy. To overcome this, the ResNet team introduced skip connections, which bypass certain layers and directly connect earlier layers to later ones. These connections ensure the flow of gradients during training, preserving essential information and making it easier for the network to learn. This innovative approach allowed ResNet to train networks with up to 152 layers effectively.

The impact of ResNet was groundbreaking. The architecture achieved a 3.57% error rate on the challenging ImageNet dataset and secured first place in prestigious competitions like ILSVRC and COCO object detection challenges. These achievements underscored ResNet's power in feature extraction and deep learning performance.

ResNet-50, a specific implementation of the ResNet model, consists of 50 layers organized into 5 blocks. Each block contains a series of residual blocks that use skip connections to retain information from earlier layers. This architecture enables the network to learn robust and detailed representations of input data, making it one of the most influential and widely adopted CNN architectures in modern AI applications.

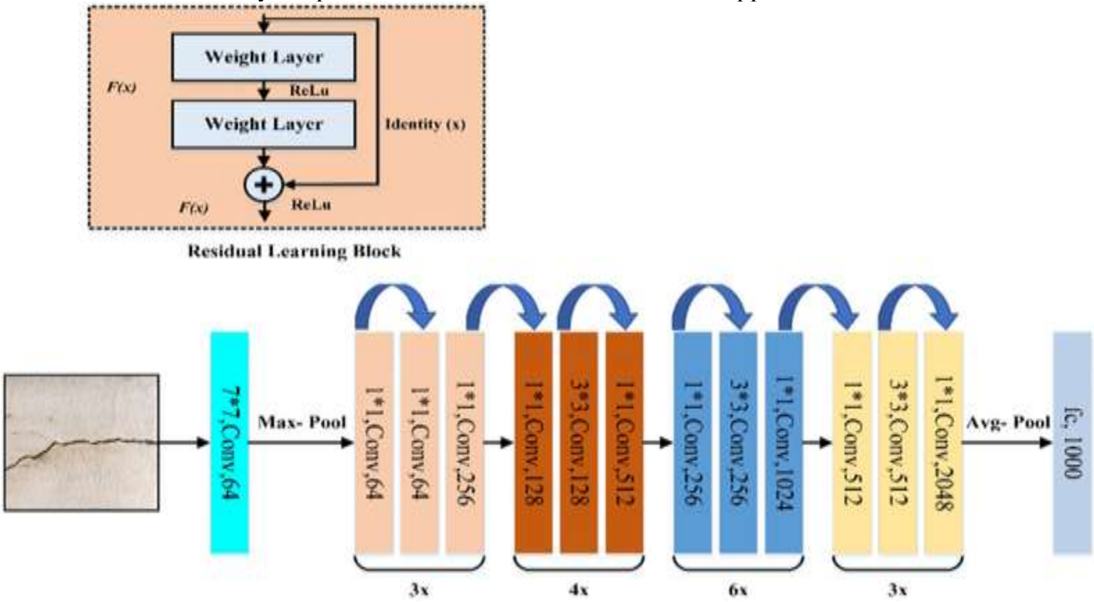

Figure 5: ResNet-50 Architecture

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RESULTS AND DISCUSSION

Performance Metrics

The performance of the model is analyzed by using the confusion matrix. This will specify the performance of classification models for given test data. This will specify the values for test data that are known. This matrix is divided into two attributes such as predicted values and original values along with an overall number of predictions.

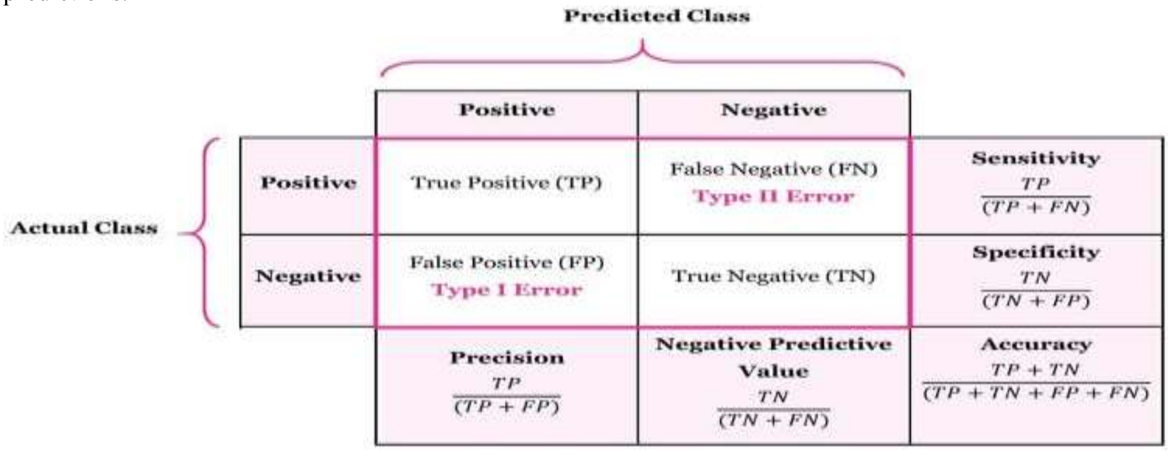

Figure 6: Confusion Matrix

True Negative (TN): The prediction value is false and actual value is also false.
True Positive (TP): The prediction value is true and actual value is false. *False Positive (FP):* The predicted value is true and actual value is false. *False Negative (FN):* The predicted value is false and actual value is true.

Evaluating the performance of a machine learning model, especially in classification tasks, involves using several quantitative metrics. These metrics provide insights into how well the model is making predictions, identifying patterns, and differentiating between various classes. The selection of appropriate metrics depends on the dataset characteristics, the problem's complexity, and the goals of the model. In this study, multiple performance metrics are employed to comprehensively assess the effectiveness of the proposed model.

Accuracy

Accuracy is one of the most common metrics used to measure classification performance. It is calculated as the ratio of correctly classified samples to the total number of samples. While accuracy provides a general overview of model performance, it may not be sufficient for datasets with class imbalances. In scenarios where one class significantly outnumbers others, accuracy can be misleading, making it necessary to consider other metrics for a balanced evaluation.

Precision

Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. It is particularly useful in applications where false positives are costly or undesirable. In the context of lung cancer detection, high precision ensures that patients diagnosed as having cancer are indeed positive cases, reducing unnecessary medical procedures and anxiety. Precision is calculated using the formula:

Recall (Sensitivity)

Recall, also known as sensitivity or true positive rate, quantifies the ability of the model to correctly identify all actual positive instances. High recall is critical in medical applications like cancer detection, where missing a diagnosis can have severe consequences. A model with high recall ensures that most positive cases are detected, minimizing false negatives.

F1 Score

The F1 Score is the harmonic mean of precision and recall, providing a balanced measure when both false positives and false negatives are significant. It is particularly beneficial when class imbalances exist. A higher F1 score indicates a better balance between precision and recall.

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Specificity

Specificity measures the proportion of correctly identified negative cases out of all actual negatives. It is especially useful when false positives are a major concern. In medical diagnostics, high specificity ensures that healthy individuals are not incorrectly diagnosed with a disease. Specificity complements recall by providing insights into the model's ability to avoid false alarms.

False Alarm Rate (FAR)

False Alarm Rate, also known as the False Positive Rate (FPR), is the proportion of actual negative cases that are incorrectly classified as positive. A lower FAR is desirable, particularly in applications where false positives can lead to unnecessary interventions or resource utilization.

Area Under the Curve (AUC) - Receiver Operating Characteristic (ROC)

The ROC curve is a graphical representation of the model's diagnostic ability by plotting the True Positive Rate (Recall) against the False Positive Rate. The Area Under the Curve (AUC) measures the overall performance of the model. AUC values closer to 1 indicate superior model performance. It is particularly useful for comparing models and determining optimal thresholds for classification.

Confusion Matrix

A confusion matrix provides a detailed breakdown of the model's predictions, showing the number of true positives, true negatives, false positives, and false negatives. It serves as a valuable tool for understanding classification errors and refining model performance. Visualizing the confusion matrix often helps in diagnosing model weaknesses and identifying opportunities for improvement.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Table 5.1: Comparative performances for detection and classification of Fruit Classifier

Algorithms	Training Accuracy	Testing Accuracy
CNN	94.26	97.23
MobileNet,	91.29	87.00
VGG-19,	96.56	96.58
Inception-v3	99.80	98.47
ResNet-50	98.01	97.78

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Comparison of Algorithms Based on Training and Testing Accuracy

Evaluating the performance of different deep learning models is crucial in understanding their effectiveness in image classification tasks like lung cancer detection. The models used in this study — CNN, MobileNet, VGG-19, Inception-v3, and ResNet-50 — exhibit varying levels of accuracy in both training and testing phases. Training accuracy indicates how well the model has learned from the training data, while testing accuracy reflects the model's generalization ability on unseen data.

CNN Performance

The Convolutional Neural Network (CNN) achieved a training accuracy of 94.26% and a testing accuracy of 97.23%. While the model demonstrates good generalization, the slightly lower training accuracy suggests it might have faced some challenges in capturing all underlying patterns. However, the higher testing accuracy indicates robust performance in real-world applications, making it a reliable choice for medical image analysis.

MobileNet Performance

MobileNet, designed for lightweight applications with limited computational resources, achieved a training accuracy of 91.29% and a testing accuracy of 87.00%. The lower testing accuracy implies potential underfitting, where the model struggles to generalize well. While MobileNet is beneficial for mobile and embedded systems, its reduced accuracy may limit its applicability in critical tasks like cancer diagnosis where higher precision is essential.

VGG-19 Performance

VGG-19, a deeper architecture with 19 layers, demonstrated impressive results with a training accuracy of 96.56% and a testing accuracy of 96.58%. The close alignment between training and testing accuracy suggests that VGG-19 generalizes well and avoids overfitting. Its ability to capture complex features with its deeper architecture makes it a strong contender for medical imaging tasks.

Inception-v3 Performance

Inception-v3 emerged as the top performer, with a remarkable training accuracy of 99.80% and a testing accuracy of 98.47%. The model's sophisticated inception modules allow it to efficiently capture intricate patterns by using multi-scale convolutions. Its near-perfect training accuracy suggests excellent feature extraction capabilities, while its high testing accuracy highlights its robustness in detecting lung cancer with minimal errors.

ResNet-50 Performance

ResNet-50 achieved a training accuracy of 98.01% and a testing accuracy of 97.78%. The use of residual blocks in its architecture enables it to train deeper networks without suffering from vanishing gradients. The slight difference between training and testing accuracy indicates strong generalization capabilities. ResNet-50's performance makes it a reliable choice for medical image classification, especially when accuracy and interpretability are critical.

While all models demonstrated significant performance, Inception-v3 and ResNet-50 outperformed others in terms of both training and testing accuracy. CNN and VGG-19 also showed commendable results, making them suitable for scenarios where computational efficiency is not a constraint. On the other hand, MobileNet, though efficient, exhibited lower accuracy, making it less suitable for critical applications like lung cancer diagnosis. The choice of the most suitable model ultimately depends on the specific requirements of accuracy, speed, and resource availability.

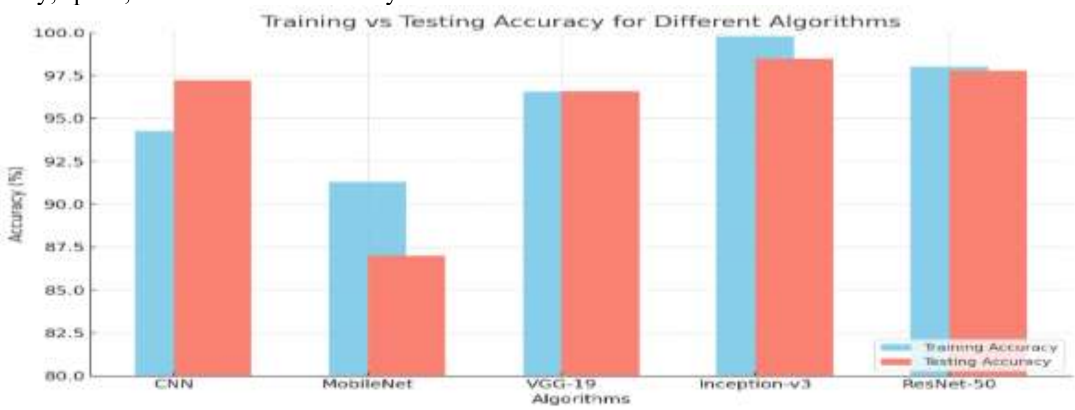

Figure 7: Comparative performances of various DL Algorithms

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CONCLUSION

In summary, the comparative analysis of deep learning models reveals notable performance differences between various architectures. With a training accuracy of 99.80% and a testing accuracy of 98.47%, Inception-V3 outperforms all other models in terms of learning capacity and generalization. With 98.01% training accuracy and 97.78% testing accuracy, ResNet-50 likewise exhibits strong performance. The CNN model comes in second with 94.26% and 97.23%, respectively. With nearly equal training and testing accuracies of 96.56% and 96.58%, VGG-19 exhibits steady and reliable performance with little overfitting. MobileNet, on the other hand, performs the worst, with 91.29% training accuracy and 87.00% testing accuracy, indicating a compromise between accuracy and efficiency. Overall, the findings show that sophisticated architectures like Inception-V3 and ResNet-50 are very successful at accurately and consistently classifying images, making them appropriate for practical uses.

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