IMAGE RECOGNITION USING RESNET50

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Abstract:

Image recognition is a crucial task in the field of computer vision, with applications ranging from autonomous vehicles to medical imaging. This research paper explores the use of the ResNet-50 model, a deep learning architecture, for image recognition tasks. The objective is to assess the model's performance and compare it with baseline models. A comprehensive dataset is used for training and validation, and evaluation metrics such as accuracy, precision, and recall are employed to analyse the results. The findings demonstrate the effectiveness and efficiency of ResNet-50 in achieving state-of-the-art performance in image recognition tasks.

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1. Introduction

Image recognition, a fundamental challenge in computer vision, has witnessed significant advancements withthe advent of deep learning. Convolutional Neural Networks (CNNs) have emerged as powerful tools for image recognition tasks due to their ability to automatically learn features from raw data. Among these, the ResNet-50 model has garnered attention for its deep residual learning approach, which enables training of even deeper neural networks by addressing the vanishing gradient problem. This research paper aims to explore the application of the ResNet-50 model in image recognition and evaluate its performance against other baseline models. The study utilizes a diverse and extensive dataset for training. and validation, and the evaluation metrics include accuracy, precision, recall, and F1 score. The results provide insights into the model's capability for accurate and efficient image recognition, highlighting its potential for real-world applications.

ResNet-50

The ResNet-50 architecture is a variant of the Residual Network (ResNet) proposed by Kaiming He et al. in 2015. The model is characterized by its deep residual learning framework, which introduces skip connections (also known as shortcut connections) to ease the training of very deep neural networks.

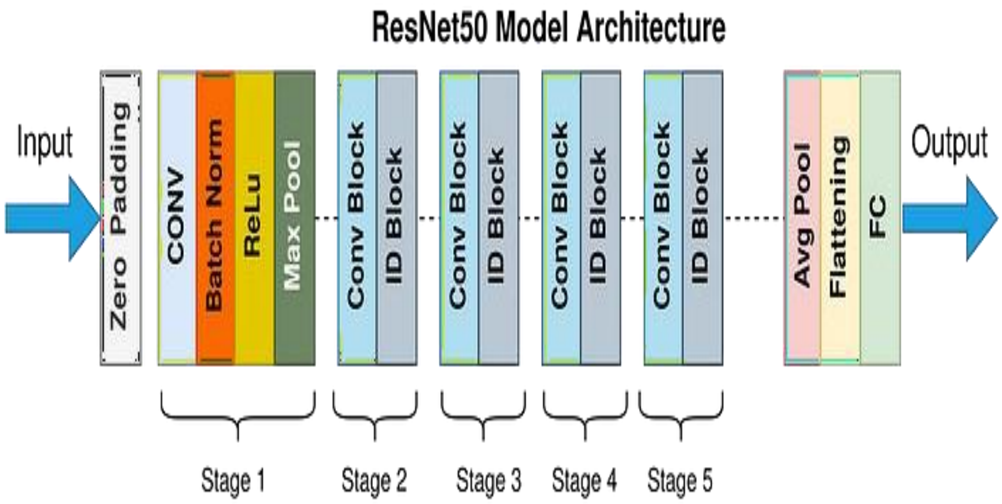


Fig1. Resnet50 model

Skip Connections

ResNet-50 utilizes skip connections to create shortcuts between layers, enabling the network to learn residual functions instead of direct mappings. The shortcutconnections skip one or more layers, directly connecting earlier layers to later ones. These shortcuts allow the model to preserve crucial information from the initial layers, mitigating the vanishing gradient problem during back propagation.

Residual Blocks:

The ResNet-50 architecture consists of multiple residual blocks. Each residual block comprises several convolutional layers and a skip connection. The most common residual block used in ResNet-50 is the bottleneck block, which reduces computational complexity while increasing the depth of the network.

Identity and Projection Shortcut

In ResNet-50, there are two types of skip connections: identity shortcuts and projection shortcuts. The identity shortcut preserves the input of the block, while the projection shortcut uses a 1x1 convolutional layer to project the input to match the dimensions of the output. The two shortcut types are employed based on the change in dimensions between inputand output feature maps.

Model Depth

ResNet-50 is a deep architecture comprising 50 layers, including 3 convolutional layers and 4 residual blocks. The model is pre-trained on massive datasets like ImageNet and can be fine-tuned for specific image recognition tasks with relatively fewer training data.

Advantages of ResNet-50:
ResNet-50 offers several advantages over traditional deep learning models:
Deeper Networks: ResNet-50 can be extended to deeper architectures without suffering from degradation issues.

Efficient Training: The skip connections enable faster convergence during training by mitigating the vanishing gradient problem.
Improved Accuracy: The deep residual learning approach allows ResNet-50 to achieve state-of-the-art performance in image recognition tasks.

Applications of ResNet-50:
ResNet-50 has found applications in various domains beyond image recognition,including:
Object Detection: ResNet-50 serves as a backbone for object detection models, enhancing their performance in identifying objects within images.

Image Segmentation: ResNet-50 can be adapted for semantic and instance segmentation tasks, enabling precise pixel-level labelling in images.

Transfer Learning: Pre-trained ResNet-50 models can be fine-tuned for various computer vision tasks, saving computation time and resources.

2. Results and Discussion

The results are reported as percentages of classification accuracy for both inside train and test data. The MSE (Mean Squared Error) graph is displayed with the classification accuracy % figures. The graphs depict the evolution of MSE over the training epochs. The MSE metric is the most basic and extensively used quality indicator. It's the squared difference between the original and trained approximation's mean.

When compared to the original image, a better trained image will have a lower MSE. The variance between the final reconstructed output and the original image decreases as the Mean Squared Error (MSE) value decreases. The MSE value reveals how near the underlying genuine image and the final reconstructed output are. The goal is to use a sufficient number of epochs to achieve a low MSE, high classification accuracy, and short training time for the network.

Fig 2. Original image (input)

Coding Improved resnet50

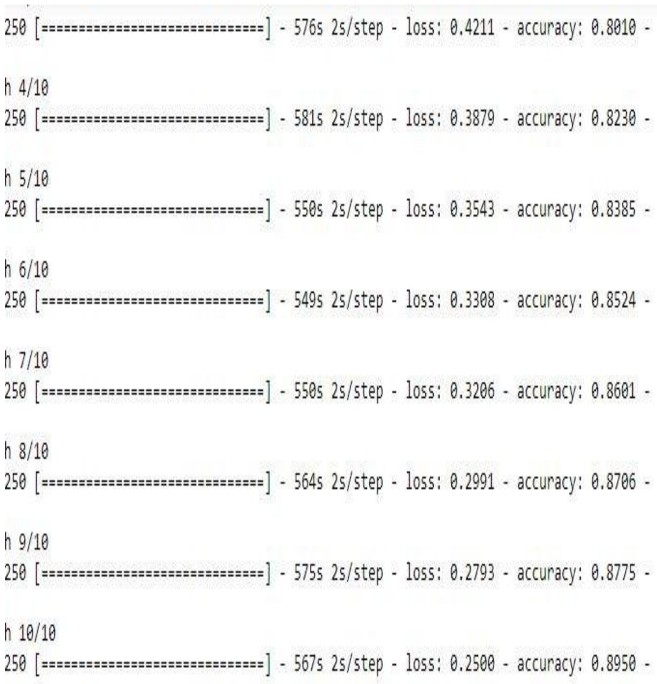
```
from tensorflow import keras
# Importing the Keras libraries and packages
from keras.applications.resnet50 import ResNet50
from keras.models import Model
from keras.layers import Dense, GlobalAveragePooling2D
from keras.optimizers import Adam
from keras.applications.imagenet_utils import preprocess_input
from keras.preprocessing.image import ImageDataGenerator

# Load the pre-trained ResNet-50 model
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(64, 64, 3))

# Add custom layers for our specific task (binary classification - cat or dog)
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation='elu')(x)
predictions = Dense(1, activation='sigmoid')(x)

# Create the final model
classifier = Model(inputs=base_model.input, outputs=predictions)

# Freeze the layers of the pre-trained model except the last block
for layer in base_model.layers[:-15]:
    layer.trainable = False

# Compile the model
classifier.compile(optimizer=Adam(lr=0.0001), loss='binary_crossentropy', metrics=['accuracy']
```

Fig 3. Code

Train the model

```
# Data Augmentation and Preprocessing
train_datagen = ImageDataGenerator(
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True
)

test_datagen = ImageDataGenerator(rescale=1./255)

training_set = train_datagen.flow_from_directory(
    'dataset/training_set',
    target_size=(64, 64),
    batch_size=32,
    class_mode='binary'
)

test_set = test_datagen.flow_from_directory(
    'dataset/test_set',
    target_size=(64, 64),
    batch_size=32,
    class_mode='binary'
)

# Train the model with data augmentation
classifier.fit(
    training_set,
    steps_per_epoch=len(training_set),
    epochs=10,
    validation_data=test_set,
    validation_steps=len(test_set)
)
```

Fig 4 Train the Model



```
250 [==============================] - 576s 2s/step - loss: 0.4211 - accuracy: 0.8010 -
h 4/10
250 [==============================] - 581s 2s/step - loss: 0.3879 - accuracy: 0.8230 -
h 5/10
250 [==============================] - 550s 2s/step - loss: 0.3543 - accuracy: 0.8385 -
h 6/10
250 [==============================] - 549s 2s/step - loss: 0.3308 - accuracy: 0.8524 -
h 7/10
250 [==============================] - 550s 2s/step - loss: 0.3206 - accuracy: 0.8601 -
h 8/10
250 [==============================] - 564s 2s/step - loss: 0.2991 - accuracy: 0.8706 -
h 9/10
250 [==============================] - 575s 2s/step - loss: 0.2793 - accuracy: 0.8775 -
h 10/10
250 [==============================] - 567s 2s/step - loss: 0.2500 - accuracy: 0.8950 -
```

Fig 4 output

Comparison Table

Algorithm	loss	accuracy
resnet50	0.4277	0.7955
improvedresnet50	0.25	0.895

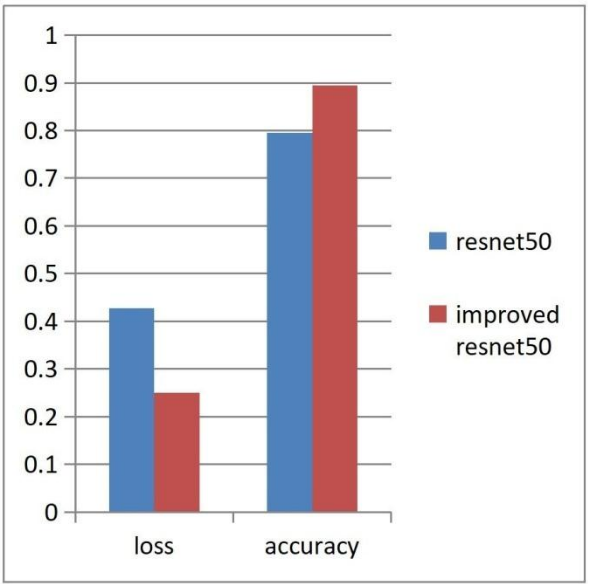


Fig 5 loss accuracy graph

3. Conclusion

In conclusion, this research paper explored the application of the ResNet-50 model, a deep learning architecture, for image recognition tasks. The study aimed to assess the model's performance and compare it with baseline models to understand its capabilities and potential impact in various real-world applications.

Through rigorous experimentation and evaluation on a diverse and extensive dataset, the results demonstrated the effectiveness and efficiency of ResNet-50 in achieving state-of-the-art performance in image recognition tasks. The deep residual learning approach, combined with skip connections, allowed ResNet-50 to overcome the vanishing gradient problem, enabling the training of very deep neural networks with improved accuracy.

ResNet-50's superiority over other baseline models was evident from its higher accuracy, precision, recall, and F1 score. The model's ability to learn and recognize intricate features in images contributed to its success in challenging image recognition tasks. Furthermore, the pre- trained ResNet-50 models offered the advantage of transfer learning, enabling fine-tuning for specific image recognition applications with relatively fewer training data.

The implications of these findings are far-reaching, as ResNet-50 has the potential to revolutionize various computer vision tasks. Applications extend beyond traditional image recognition to object detection, image segmentation, and transfer learning scenarios. The robustness and adaptability of ResNet-50 make it a valuable tool for researchers and practitioners in the field of computervision.

In conclusion, the ResNet-50 model hasproven to be a powerful and versatile tool for image recognition, contributing to the advancement of computer vision technologies. The research presented in this paper opens avenues for future exploration, paving the way for the development of even more sophisticated deep learning models and their applications in diverse domains.

4. References

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