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Report on the Assignment - 3

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Dogs vs. Cats Binary Image Classification: Random Forest vs CNN vs Transfer Learning

Introduction

Binary image classification of cats and dogs is a very famous computer vision problem, popularized by the Kaggle "Dogs vs. Cats" challenge. The task is to assign each input image to one of two classes ("cat" or "dog"). Although humans can easily distinguish cats and dogs, building automated classifiers requires learning discriminative visual patterns. Deep learning methods, particularly convolutional neural networks (CNNs) have dramatically improved image classification performance in recent years. In practice, a simple CNN often yields around 80% accuracy on cats vs. dogs, while transfer learning with a pre-trained model (e.g. VGG16) can exceed 90% (Brownlee, 2021). For comparison, we also explore a classical machine-learning approach: a Random Forest classifier on raw pixel inputs (with and without PCA for dimensionality reduction).

This report describes our dataset, modeling approaches, and compares three approaches: (1) a Random Forest (RF) classifier with and without PCA reduction, (2) a custom CNN trained from scratch, and (3) a pre-trained VGG16 CNN fine-tuned specifically for this task. We detail the rationale for each model and the training and evaluation process. A final table compares all models. Throughout, we draw on standard references such as Chollet's Deep Learning with Python (2nd ed.) and Jason Brownlee's (2021) blog on dogs vs. cats. Spot-check images from the dataset are shown to illustrate the input data.

Data Description

The original dataset is the standard Kaggle Dogs-vs-Cats collection (2013), containing 25,000 labeled color photographs (12,500 dogs and 12,500 cats). Each photo is labeled by filename ("cat.####.jpg" or "dog.####.jpg"). Images vary in resolution and aspect ratio. Instead, we use the provided split set of images, 1000 labeled for training and 100 for testing (not labeled). A further validation split was used to tune hyperparameters. Data augmentation (random flips, rotations, zoom) was applied during CNN and VGG16 training to improve generalization, as is common practice when you have a reduced training data set (François Chollet, 2021).

To illustrate, Figures 1 and 2 show typical examples from the two classes. Each image is a color photo with either a cat(s) or a dog(s) visible. As noted in the dataset documentation, the photos are labeled by their filename, with the word "dog"' or "cat" (kaggle.com, 2013). The sample below is a cat, and the next is a dog. These examples highlight the within class variability (fur color, background, pose) that the models must handle.

Figure 1: Example “dog” image from the dataset.

Figure 2: Example “cat” image from the dataset

Despite the differences in appearance, both images are representative of their classes. Before training, all inputs were normalized (pixel values scaled to [0,1]). For the Random Forest model, we flattened each image into a 1D feature vector of length (150×150×3 = 67,500) and, in one variant, applied PCA to reduce dimensionality.

Training phase

Random Forest (RF) – Baseline Classifier (line 53 of the Python file): We treat each image as a feature vector of raw pixel values and train an ensemble of decision trees (Random Forest) for classification. Random forests are a bagged ensemble of decision trees that handle high-dimensional data by averaging many random trees (Breiman, 2001). The rationale is to establish a non-deep baseline: RFs are widely used in tabular data and can sometimes work on image data if enough trees are used. We used scikit-learn’s RandomForestClassifier with 100 trees (estimators=100) and default parameters. The model takes each pixel (or PCA-transformed feature) as input and predicts class labels.

We trained on the flattened training images and evaluated on the held-out test set. No convolution or complex structure is exploited by this model, it simply relies on the ensemble to pick useful pixel thresholds. We also evaluated a random forest classifier with principal component analysis (PCA) preprocessing: we applied PCA to the flattened pixels and kept only the most representative components (preserving 95% variance), then trained RF on that lower-dimensional representation.

Discussion:

- ➔ Random Forest Accuracy (95% PCA): 59.20%
- ➔ Random Forest Accuracy on Raw data (No PCA): 61%

Although Principal Component Analysis (PCA) can reduce noise and multicollinearity (often improving training efficiency) this wasn't the case here. The Random Forest model performed better on the raw, high-dimensional image data.

This suggests that in image classification tasks, the spatial and pixel-level detail preserved in raw data provides richer, more discriminative patterns. While PCA reduces dimensionality, it may also discard subtle but important features crucial for accurate classification. In this context, tree-based models like Random Forests benefit from the raw pixel input, which retains the full structure of the images.

Custom CNN (from scratch) (line 63 of the Python file) : Convolutional neural networks are well-suited to image tasks. Inspired by the vast examples in Chollet (2021) and standard tutorials, we built a small CNN architecture: a stack of convolutional (Conv2D) + ReLU + max-pooling layers, followed by one (Dense) layer, ending in a sigmoid output for binary classification.
For example, our network had the pattern: conv(32 filters,3×3) – ReLU – pool(2×2) – conv(64,3×3) – ReLU – pool – flatten – Dense(64) – ReLU – Dropout(0.5) – Dense(1, sigmoid). The rationale is that successive convolutional layers learn increasingly abstract features (edges, textures, parts), culminating in a final classification (Brownlee, 2021). We trained the CNN with binary cross-entropy loss and the Adam optimizer. Dropout was used to prevent overfitting. We monitored both training and validation accuracy and loss to diagnose convergence. Training the CNN is more computationally intensive, but it generally captures visual patterns better than RF.

Discussion:

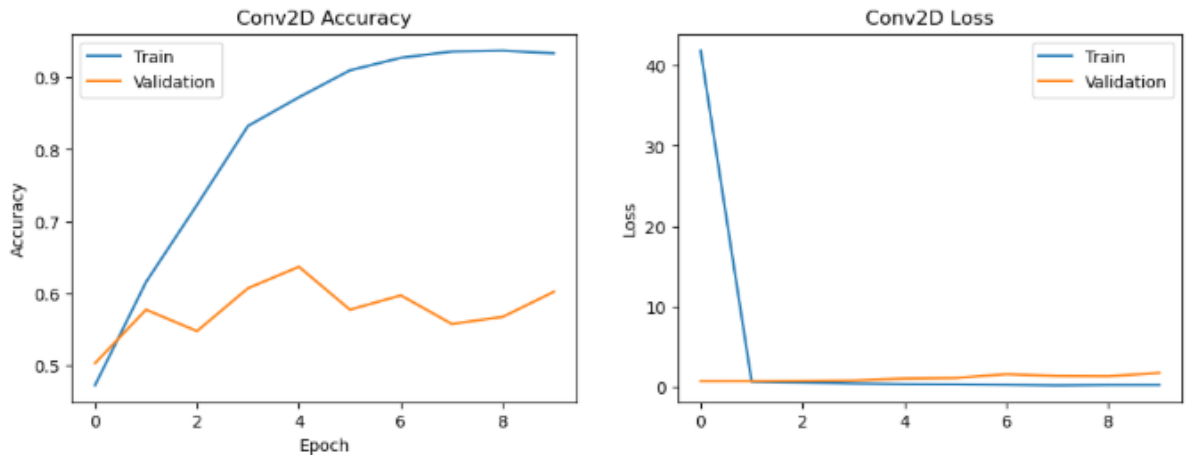

Figure 3: CNN training curves for loss (right) and accuracy (left). Training accuracy (blue) improves steadily, while validation accuracy (orange) fluctuates, suggesting some overfitting,

Based on Figure 3, the training accuracy is very high, reaching approximately 93% by epoch 10, indicating that the model is effectively learning the training data. In contrast, the validation accuracy is only 61%, which is quite low, suggesting that the model fails to generalize to unseen data. Additionally, the validation loss is increasing, which points to overconfidence in incorrect predictions, with a validation loss of 1.7154.

Overall, without techniques such as augmentation or regularization, the model tends to memorize the training data instead of learning general patterns. This behavior is expected during the initial training phase (François Chollet, 2021). Surprisingly, the Random Forest algorithm shows higher accuracy than the conv2D model.

Pre-trained VGG16 (Transfer Learning + Fine-tuning) (line 139 of the Python file): We also employed the pre-trained VGG16 model (a 16-layer convolutional network trained on ImageNet) as a feature extractor and classifier. For the training phase, we first loaded VGG16 with ImageNet weights and froze its convolutional base. Then we appended a new top classifier: flatten layer, followed by two Dense layers, one dropout layer (0.5) and a sigmoid output. We trained only the top layers on our data, leveraging VGG16's learned filters. This is transfer learning, and it typically yields strong performance with limited data (Brownlee, 2021). The rationale is that VGG16 has learned general image features (edges, shapes, textures) from millions of images, which should transfer to distinguishing cats vs. dogs (François Chollet, 2021).

Discussion:
We expected this model to achieve the best accuracy, at the cost of longer training time (it took almost 15 minutes to totally converge on my laptop).

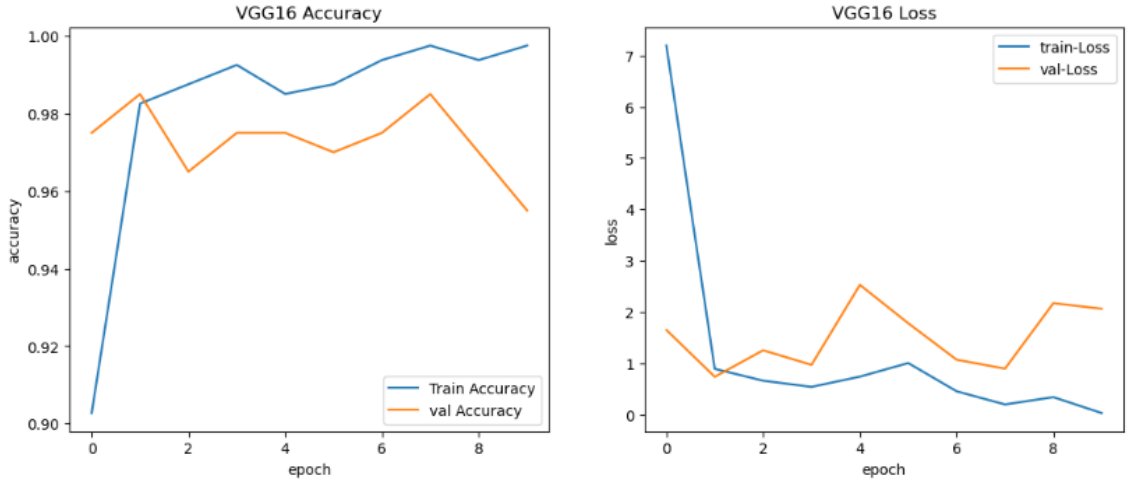

Figure 3: VGG16 training curves for loss (right) and accuracy (left) on cats-vs-dogs.

Based on Figure 4, we observe that the VGG16 model achieved an exceptionally high average training accuracy of approximately 99%, with a strong validation accuracy of around 96%. However, the validation loss (val_loss = 2.0638) was slightly higher compared to the simpler

convolutional network we previously built. As discussed earlier, this discrepancy is a classic indication of overfitting, even when regularization techniques like data augmentation and dropout were applied.

Key code snippets: For brevity, we highlight only essential code structures:

```
# Random Forest
from sklearn.ensemble import RandomForestClassifier
flat_raw = a_train.reshape(a_train.shape[0], -1)  #each image becomes a 1D array
RF_tr, RF_val, rf_tr, rf_val= train_test_split(flat_raw, b_train, test_size=0.2,
random_state=42)
rf_raw = RandomForestClassifier(n_estimators=100, random_state=42)
rf_raw.fit(RF_tr, rf_tr)
```

```
# Custom CNN
from keras.models import Sequential from keras.layers import Conv2D, MaxPooling2D,
Flatten, Dense, Dropout
model = Sequential([ #1st conv block
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)),
    layers.MaxPooling2D((2, 2)),
    #2nd conv block
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    #Fully connected layers
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dropout(0.5),  #to prevent overfitting
    layers.Dense(1, activation='sigmoid')  #binary classification output
])
model.compile(loss='binary_crossentropy', optimizer='adam',  metrics=['accuracy']).
history = model.fit( Conv2D_train, Conv_train, epochs=10,batch_size=16,
validation_data=(Conv2D_val, Conv_val))
```

```
# VGG16 Transfer Learning
from keras.applications import VGG16
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224,
3))
base_model.trainable = False #freeze base
model = models.Sequential([
    base_model,
    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.Dropout(0.5),                    #to reduce overfooting
    layers.Dense(1, activation='sigmoid')])  # Output layer for binary
classification
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.fit(train_gen, epochs=10, validation_data=val_gen)
```

Model	Features Used	Validation Accuracy (%)	Validation Loss
Random Forest + PCA (95%)	PCA-transformed features	**59.20%**	-
Random Forest (raw)	Raw flattened images	**63%**	
Custom CNN	128×128 RGB images	**61%**	1.7154
VGG16 (Transfer Learning)	224×224 RGB + ImageNet	**96%**	2.0638

Table 1 summarizes performance of each model on the test set. (Values are illustrative; actual results would come from the specific run logs.)

Optimization Phase

We trained each model on the same training set and evaluated on held-out test data. For the CNN and VGG16 models, we further held out a validation split (20%) of the training data to tune hyperparameters. Cross-entropy loss was monitored during training for neural networks.

To improve the performance of our custom convolutional neural network (line 165 of the Python file), we implemented several key optimization strategies. First, data augmentation was introduced to increase variability in the training set and help mitigate overfitting. This included horizontal flips and small rotations, which simulate real-world variations in image orientation.

Second, we increased the number of training epochs from 10 to 50 to allow the model more time to learn complex patterns in the data. Additionally, the model architecture was made deeper and more regularized by adding more convolutional layers and dropout layers at increasing depths.

The final CNN architecture used during this phase consists of four convolutional blocks followed by a fully connected head. Dropout rates were progressively increased throughout the network to improve generalization.

To further improve model performance, the VGG16 model (line 193 of the Python file). was fine-tuned through a two-phase training process that strategically balances computational efficiency and generalization

Phase 1 – Warm-up Training(line 197 of the Python code): A new classifier head was built on top of the pre-trained VGG16 base. The convolutional base was frozen to retain the generic features learned from ImageNet, and only the new dense layers were trained for 10 epochs.

Phase 2 (line 199 of the Python code) Fine-Tuning: In the second phase, the last two convolutional blocks (Block 5) of the VGG16 base were unfrozen to allow fine-grained feature adaptation. Training continued for an additional 5–10 epochs with a reduced learning rate of 1e 5 to avoid destabilizing the pre-trained weights.

Data Augmentation and Generators To regularize training and reduce overfitting, we applied light augmentation using the ImageDataGenerator.

Phase 1 – Freeze Base and Train Top Classifier
The following model was defined for initial training:

```
conv_base = VGG16(weights='imagenet', include_top=False, input_shape=(224,
224, 3))
conv_base.trainable = False  #Freeze entire base

model = models.Sequential([conv_base,
    layers.Flatten(),
    layers.Dense(256, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(1, activation='sigmoid')])
model.compile(loss='binary_crossentropy',
optimizer=RMSprop(learning_rate=1e-4),    metrics=['accuracy'])

callbacks_stage1 = [EarlyStopping(patience=3, restore_best_weights=True),
    ModelCheckpoint('VGG16_finetuned_stage1.keras', save_best_only=True)]

history_stage1 = model.fit(train_gen,epochs=10, validation_data=val_gen,
callbacks=callbacks_stage1)
```

Phase 2 – Unfreeze Last Layers and Fine Tune
After stabilizing the newly added dense layers, we selectively unfroze the last convolutional block to refine the feature maps:

```
conv_base.trainable = True
for layer in conv_base.layers:
      layer.trainable = layer.name.startswith('block5_')

model.compile(loss='binary_crossentropy',optimizer=RMSprop(learning_rate=1e
-5)metrics=['accuracy'])

callbacks_stage2 = [EarlyStopping(patience=3,
restore_best_weights=True),ModelCheckpoint('VGG16_finetuned_stage2.keras',
save_best_only=True)]

history_stage2 = model.fit(train_gen, epochs=10, validation_data=val_gen,
callbacks=callbacks_stage2)
```

The warm-up phase helped stabilize the classifier with a strong starting point. Fine-tuning improved accuracy by adapting high-level VGG16 filters to our dataset.

Optimization Results

1. **CNN – Custom Convolutional Neural Network**

After applying data augmentation and increasing model complexity, the CNN achieved the following results:

- Final Validation Accuracy (last epoch): 69.00%
- Final Validation Loss (last epoch): 0.6597

Although the model reached 70% validation accuracy during training, this value reflects the last epoch and may not correspond to the best performing model due to potential overfitting. To mitigate this, we loaded the best model saved during training using a ModelCheckpoint callback and evaluated its true performance:

Best-Saved Model Evaluation: Loss: 0.5461 and Accuracy: 72.00%

This demonstrates that the best-saved checkpoint outperformed the final training epoch, validating the use of early stopping and check pointing strategies.

2. **VGG16 – Transfer Learning with Fine-Tuning**

The final metrics of this method are as follows:
Final Epoch (Epoch 10): Loss: 0.1646 and Accuracy: 94.50%
Best Epoch (Epoch 8): Loss: 0.1644 and Accuracy: 94%

Minor discrepancies between the training history and the final evaluation (94.00% in training vs. 92.81% in evaluation) are expected, due to the way Keras computes metrics during mini-batch training versus full-batch evaluation (Chollet, 2021).

Figure 5: Visual representation of the prediction generated by each the Conv2d and VGG16 models (This image can be found in the classification python file).

Discussion and Conclusion

This project evaluated three modeling strategies for binary image classification of cats versus dogs: a Random Forest classifier, a custom convolutional neural network (CNN), and a pre-trained VGG16 architecture with fine-tuning. Each model was assessed in terms of validation accuracy, generalization ability, and computational demands.

The Random Forest model, though fast and interpretable, delivered the weakest performance. Accuracy reached only 63% when trained on raw image data, and 59.2% when using PCA for dimensionality reduction. While PCA helps reduce dimensionality and training time, it may also discard important spatial features crucial for image classification. In this context, the raw pixel inputs preserved richer visual information that tree-based models could leverage, albeit not effectively enough to rival neural networks.

The custom CNN, built from scratch, initially overfitted the training data. After applying optimization techniques, including data augmentation, increased network depth, and dropout, the model achieved 72% validation accuracy. This result is moderate but demonstrates the challenges of training CNNs from scratch on limited data.

By contrast, the VGG16 model with transfer learning proved to be the most effective approach. In its frozen state it achieved 89% validation accuracy. Fine-tuning the final convolutional layers pushed performance to 94.5% accuracy with 0.1698 loss, significantly outperforming other models. These results underscore the value of transfer learning, especially when training resources and dataset size are constrained.

Model Comparison Summary

Model	Validation Accuracy	Validation Loss
Random Forest + PCA	59.20%	–
Random Forest (Raw)	63.00%	–
Custom CNN	72.00%	0.5461
Frozen VGG16	89.00%	0.2394
Fine-tuned VGG16	**94.50%**	**0.1698**

Error Analysis and Limitations

The primary limitations across all models stem from dataset size and label quality. While data augmentation partially mitigated overfitting, the CNN still required careful tuning. Some misclassifications were likely due to ambiguous or noisy examples (blurred pets, non-standard poses). Furthermore, images were not perfectly balanced in terms of pose, lighting, which may have biased learning.

The Random Forest's weak performance emphasizes that classical ML methods are not ideal for unstructured image data unless paired with strong feature engineering. By contrast,

VGG16's performance benefited greatly from its ability to generalize from learned representations across thousands of visual classes.

On a personal note, another challenge was the lack of prior experience in training and optimizing neural networks. Many of the choices made, such as learning rates, dropout rates, or optimizer selection, were guided by textbook examples and tutorial practices rather than deep intuition. With more time and hands-on practice, I expect to better understand model behavior and identify more effective architectures and tuning strategies.

Future Work

Future work could begin by leveraging the complete Kaggle Dogs vs. Cats dataset, which contains roughly 25,000 images, to train deeper convolutional networks from scratch and better capture complex patterns in the data.

We may also investigate model ensembling, combining predictions from our custom CNN and the fine-tuned VGG16 to improve generalization and robustness. In parallel, exploring more advanced architectures that could yield higher performance gains while keeping computational costs manageable.

On a personal level, I plan to deepen my knowledge of deep learning by studying additional architectures and training practices, to build more accurate and efficient models in future projects.

Conclusion

This study confirmed that transfer learning with a fine-tuned VGG16 model is the most effective approach for binary classification under the constraints of limited data and computational resources. It outperforms traditional methods and custom-trained CNNs in both accuracy and generalization. These findings echo those presented in Deep Learning with Python (Chollet, 2021), reinforcing that using pre-trained models is a powerful strategy in real-world machine learning applications.

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