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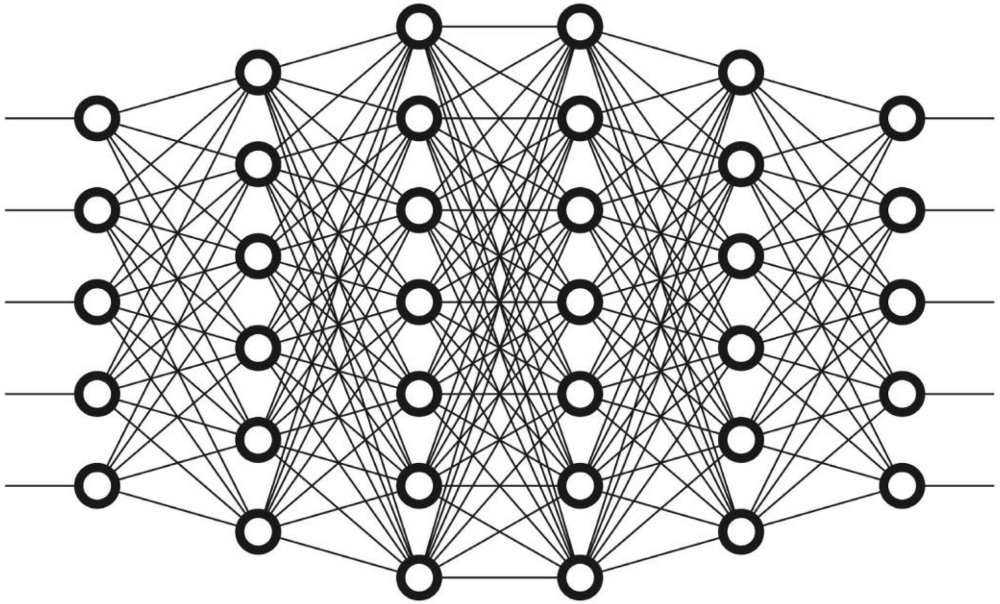
The Ringgit Classifier

Can a computer classify your Ringgits?

Introduction

- Computers have made it all possible…



Cat

Problem Statement

- Unlike coins, paper notes are not easily identified by their weight and sizes.

- Blind and visually impaired people had to rely on the identification marks which are not effective enough to let them know the money correctly.

- Lack of an existing application that enables people to recognize Malaysian Ringgit automatically and efficiently.

Project Objectives

- Develop an image classification model that supports 6 classes.
- Use the available VGG16 API and apply Transfer Learning.
- Prepare and process the datasets.
- Create an image classifier that classifies Malaysian Ringgit.

How did this idea come into fruition?

(the journey along with the challenges faced…)

The Idea (The ideas that didn't happened)

Initial Idea → Data Collection → Challenges faced

Initial Idea

- Develop an object detection model that able to detect counterfeit Malaysian bank notes.
- Found out that there is a lack of pre-existing data available on the internet.

Data Collection

- Took photos of Malaysian Ringgit using camera phones with well-lit background.
- Perform editing using Adobe Photoshop to remove the exposed watermarks to simulate the counterfeit bills.

Challenges faced

- The Tiny-YOLO model could not predict the counterfeit money.
- We found out that the "deformations" are not large enough to be predicted by the model.

The Idea (The ideas that did happened)

Data Collection → Data Processing → Architecture and Modelling

Data Collection

- Asked for the courtesy of researchers from Universiti Teknologi Malaysia (UTM).
- Obtained a sample of 673 Malaysian Ringgits comprising of RM1, RM5, RM10, RM20, RM50 and RM100.

Data Processing

- Perform image augmentation to artificially increase the amount of data samples.
- Split data into training and testing.
- Scale data with image pre-processing.

Architecture and Modelling

- Utilize the VGG16 model compared to other top performing CNN models due its simple structure.
- VGG-16 consists of 16 layers with learnable parameters.
- Fine-tune only the last few layers due to overfitting concerns.

The Idea (The ideas that did happened)

Evaluation → Results

- Compare training with testing accuracy to identify overfitting issues.

- Use smaller batches and number of epochs to overcome overfitting during the subsequent training.

Training results (epochs = 20, batch size = 15)

```
========================Evaluation Metrics========================
 # of classes:    6
 Accuracy:        0.8139
 Precision:       0.8364
 Recall:          0.8145
 F1 Score:        0.8115
Precision, recall & F1: macro-averaged (equally weighted avg. of 6 classes)


=========================Confusion Matrix=========================
  0  1  2  3  4  5
-------------------
 60  0  0  0  7  0 | 0 = RM1
  0 52  1  7  7  0 | 1 = RM10
  0  0 42  4  8 13 | 2 = RM100
  0  0  0 67  0  0 | 3 = RM20
  0  0  0  0 67  0 | 4 = RM5
  0  0 10  3 15 40 | 5 = RM50
```

```
========================Evaluation Metrics========================
 # of classes:    6
 Accuracy:        0.8439
 Precision:       0.8659
 Recall:          0.8430
 F1 Score:        0.8405
Precision, recall & F1: macro-averaged (equally weighted avg. of 6 classes)


=========================Confusion Matrix=========================
  0  1  2  3  4  5
-------------------
 29  0  0  0  0  0 | 0 = RM1
  0 22  1  3  3  0 | 1 = RM10
  0  0 18  0  7  4 | 2 = RM100
  0  0  0 29  0  0 | 3 = RM20
  0  0  0  0 29  0 | 4 = RM5
  0  0  2  2  5 19 | 5 = RM50
```

The Idea (The ideas that did happened)

Results

Training results (epochs = 10, batch size = 10)

```
========================Evaluation Metrics========================
 # of classes:    6
 Accuracy:        0.8462
 Precision:       0.8504
 Recall:          0.8464
 F1 Score:        0.8370
Precision, recall & F1: macro-averaged (equally weighted avg. of 6 classes)


=========================Confusion Matrix=========================
  0  1  2  3  4  5
-------------------
 67  0  0  0  0  0 | 0 = RM1
  2 61  1  3  0  0 | 1 = RM10
  8  0 30  1  0 28 | 2 = RM100
  0  1  0 66  0  0 | 3 = RM20
  2  0  0  0 65  0 | 4 = RM5
  1  0  6  1  8 52 | 5 = RM50
```

Testing results

```
========================Evaluation Metrics========================
 # of classes:    6
 Accuracy:        0.8382
 Precision:       0.8465
 Recall:          0.8383
 F1 Score:        0.8278
Precision, recall & F1: macro-averaged (equally weighted avg. of 6 classes)


=========================Confusion Matrix=========================
  0  1  2  3  4  5
-------------------
 29  0  0  0  0  0 | 0 = RM1
  2 23  0  4  0  0 | 1 = RM10
  3  0 12  0  0 14 | 2 = RM100
  0  0  0 29  0  0 | 3 = RM20
  0  0  1  0 28  0 | 4 = RM5
  0  0  3  0  1 24 | 5 = RM50
```

Possible Improvements

Weaknesses

- Despite a high accuracy, the result might be due to overfitting as the training and test datasets were very similar.
- The model is not trained with realistic images that allowed it to be generalized well.
- VGG16 model uses a lot of memory and parameters which requires higher computational power.
- Lack of a real-time application that user can directly interact with good user interface.

Solutions

- Obtain a larger, real-world dataset with more variations between image samples to make model more accurately trained and generalize better.
- Use different architecture to train our data set to maybe obtain a better results.
- Produce a mobile-based application for greater usability.

Project Demo

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Thank You!