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Assessment Cover Page

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| Module Title: | Advanced Data Analytics  Big Data Storage and Processing |
| Assessment Title: | Integrated CA1 Sem 2 MSc in Data Analytics |
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| Student Number: | SBS22070 |
| Assessment Due Date: | 03/10/2022 |
| Date of Submission: | 02/10/2022 |

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Image Recognition for Learning Arabic Words

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*Abstract*—IEEE format requires you to include an abstract at the start of your paper, followed by a list of keywords. In the “Styles” section in Microsoft Word, you can find the appropriate styles for all the different sections and headings in the paper, which are already applied here. For example, the “abstract” style is applied to this text, the “keywords” style to the next section. Note that the titles “Abstract” and “Keyword” should remain as they are written here: italicized and followed by an em dash.

Keywords—image classification, Arabic, big data

# INTRODUCTION

With more than 7,000 languages currently spoken [1], their study can be complex and biased by researchers’ preferences and the availability of funding. In general, languages can be grouped into families, of which there are more than 100 [2]. Arabic and English are spoken by about 360-400 million native speakers [3], [4] and are official United Nations languages [5]. However, English is a *lingua franca* through the prevalent inter-connected global economic structure [6]. Arabic is a part of the Afro-Asiatic family [7] while English is an Indo-European language [8], yet historical contact through a series of commerce and wars [9] has allowed for an intermingling (borrowing) of words. Arabic words, such as ‘sine’ and ‘alkali’ have penetrated English while words such as بلاستيك (‘bi-laastik’, plastic) have an English origin [10].

Unlike English, Arabic is an unusual language. For example, there are 200 words that refer to lion in Arabic [11]. The definite article ‘the’ in Arabic (‘al’, ال) never stands alone. Yet, when joined with another word will change its morphology (for example, lion (أسد) will become الأسد). There are also regional variations, which is why learners of Arabic usually tend to follow the Modern Standard Arabic [12].

Given the complexity of Arabic compared to English, it would be helpful for learners of Arabic, especially those who are not native, to have the ability to instantaneously convert images to Arabic words. The ubiquitous smartphones can play a significant role in helping these learners by snapping images of new objects that can be classified rapidly in Arabic.

Image recognition through deep learning is a particularly useful method for classifying images. Two types of solutions are relevant in the context of helping Arabic learners – (i) multi-class algorithms where each image is assumed to only take one label and the entire dataset consists of multiple labels, or (ii) a multi-label problem where each image can take multiple labels. Taking an image of a woman walking with a dog as an example, the image can be labelled either as a woman or a dog, but not both (multi-class), or as a woman and a dog (multi-label).

## Convolutional neural network (CNN)

CNN is a neural network that consists of one or more convolutional layer, non-linearity layer, pooling layer and finally fully-connected layer [13]. As the relative position of an object in an image is less relevant, the convolution layer allows for the extraction of features irrespective of object orientation. In fact, small datasets may be augmented by artificial shearing and rotation. Unlike recurrent neural networks, CNN is highly parallelisable especially when graphical processing units (GPUs) are used.

Image recognition is a well-studied domain of artificial intelligence with wide-ranging applications in real life. As such, complex pre-trained models have been published and are easily accessible within the TensorFlow ecosystem [14]. The use of pre-trained models hinges on the ability to adapt deep learning models across different use cases [15]. This ability, termed transfer learning, is based on how humans learn to identify new objects. A model trained on pictures of animals for a binary classification (‘is it an animal or not?’) can be used to classify the type of animal (‘what animal is it?’). Transfer learning will not be appropriate if the training dataset is completely different than the original dataset. When the datasets are similar, however, the use of pre-trained models can result in highly accurate models at a fraction of time needed for full training.

Another advantage of deep learning is that it requires no feature engineering. In the context of image classification, no annotation will be required to identify the legs or ears of an animal. This becomes useful when human cannot pre-identify features of high relevance to learning. Neural networks also lend itself to modular and complex architectures, including the ability for branching (multi-headed) training that can take advantage of distributed training (model parallelism). In this mode, one GPU may be used for one branch while another can be simultaneously used for the other branch, further reducing the total training time.

Several architectures of deep neural networks have been proposed for the use of image classification as summarised in TABLE 1. These include various MobileNet architectures [16] that originate from Google researchers, including MobileNetV2 [17] and MobileNetV3 Large [18]. These models are targeted for mobile and embedded devices where the computational power is more limited compared to personal computers. Although deeper and complex networks may achieve higher accuracy, they also require longer time and power for training. Through MobileNet architectures, the researchers aimed to create more efficient networks by using depthwise separable convolutions, which themselves are a combination of 3x3 depthwise convolution and 1x1 (pointwise) convolution [16]. MobileNetV2 builds on the original MobileNet work by including an inverted residual structure with shortcut connections between thin bottleneck layers [17]. Overall, the use of depthwise separable convolution significantly reduces computation – for instance, MobileNetV2 requires about 8 to 9 times less power than standard convolution [16]. The bottleneck layers accept a low-dimensional compressed representation, which is then expanded to a high dimension and filtered with depthwise convolution (Fig. 1).

In deep learning, it can be difficult to judge whether one architecture will be better than the other. The use of network architecture search (NAS) is essentially ‘a neural network to design a neural network’ as it automated the manual search for the optimal architecture [19]. MobileNetV3-Large is a product of NAS and network design, with the resulting increase of 3.2 % in accuracy on ImageNet classification with 20 % reduction of latency compared to MobileNetV2 [18].

Diagram

Description automatically generated

Fig. 1. Evolution of MobileNet networks through the use of separarable and bottleneck layers. Diagonal hatches indicate linear layers. The final (lightly coloured) layer is also the beginning of the next block. Upon stacking, the blocks in (c) and (d) are equivalent. Figure taken from [17].

Another family of relation architectures is the Inception network, including InceptionV3 [20] and InceptionResNetV2 [21]. This family is also aimed at simplifying network structure for its use in mobile and other low performant devices. The Inception networks arose from architectural considerations around convolutional layers as well as balancing of the network width and depth. In general, convolutions with spatial filters larger than 3x3 tend to be more computationally expensive. Nevertheless, they can capture long-range dependencies [20]. As a workaround, a multi-layer network with 3x3 convolutions was proposed with a resulting network depth of 42 layers for InceptionV2. InceptionResNetV2 extends the thinking further by incorporating residual connections, which was first introduced in [22] to reduce training time.

The NasNetMobile architecture [23] also uses NAS to design the best model where accuracy was increased by 1.2 % with a concomitant reduction in computation of 28 %. The NAS search space was limited to only the best cell structure instead of re-designing the entire architecture. Further limits were also placed on activation (ReLU only) and no batch normalisation/ReLU for depthwise separable convolution. The VGG19 (Visual Geometry Group 19 weight layers) [24] is one of the two models that take advantage of depth as the main driver for image recognition algorithms through the use of very small (3x3) spatial filters. In contrast, the Xception network [25] was propositioned as an interpretation of the Inception module, forming an intermediate between regular convolution and depthwise separable convolution. Both InceptionV3 and Xception have the same number of parameters but performance gains in the latter were achieved through a better use of parameters.

|  |  |  |
| --- | --- | --- |
| **Model** | **Number of parameters** | **Commentary** |
| InceptionV3 | 23.9M | Captures long-range relationships through deep small spatial filter layers, instead of large spatial filters. |
| InceptionResNetV2 | 55.9M | Incorporates residual connections to reduce training time. |
| MobileNetV2 | 3.5M | Adds bottleneck layers with separable layers. |
| MobileNetV3-Large | 1.4M | Used NAS to arrive at the optimal architecture. |
| NasNetMobile | 5.3M | Used optimised design space for NAS. |
| VGG19 | 143.7M | Deep CNN with 19 layers. |
| Xception | 22.9M | Improvement over InceptionV3. |

TABLE I.

SUMMARY OF VARIOUS NEURAL NETWORK ARCHITECTURES FOR IMAGE CLASSIFICATION.

## Big image data

Success of deep learning research depends on the availability of large datasets. As shown in TABLE 1 above, these architectures consist of millions of trainable parameters, necessitating the use of large training datasets. Fortuitously, public image datasets are available, allowing for like-for-like comparison of various image classification algorithms. A popular dataset often used as the standard for benchmarking is ImageNet, a database of more than 14 million images organised according to the WordNet hierarchy [26], [27]. The hierarchy organises over 150,000 words into 117,000 synsets (synonym sets/categories), thereby establishing ontological and lexical relationships for natural language processing tasks [28]. For instance, German shepherd is organised under ‘dog’, which in turn is under ‘mammal’, potentially allowing for the same images to be used for different model training depending on the requirements (‘cats *vs*. dogs’, or ‘what breed of dog is this?’) More than 20,000 synsets have been indexed in ImageNet. To help the research community, a subset of the dataset has been human annotated using Amazon Mechanical Turk [27], which also forms the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) dataset [29].

In contrast to ImageNet, the Massively Multilingual Image Dataset (MMID) consists of 98 languages and 10,000 words per language [30]. The images were collected using Google Image Search, which has a major disadvantage of being prone towards highly optimised webpages. Search engine optimisation is a digital marketing strategy that could lead to bias in the type of images being included in the dataset, although the authors performed a filtering step. Unlike ImageNet, the words are not limited to nouns although nouns and adjectives were found to be translated with significantly higher accuracy than verbs and adverbs [30]. For example, searching for coffee could result in images of cups and mugs and not necessarily coffee powder. MMID is also not hand-annotated, which could represent a more realistic opportunity for automated learning by algorithms. Searching for images in a target language may result in images that are biased towards the demographics of native speakers. By default, Google Image Search filters inappropriate search results, which can remove the ability of researchers to use the dataset for an automated image flagging algorithm.

As will be demonstrated in later sections, the Arabic language is highly complex and requires an understanding of grammar. The MMID dataset is significantly less researched than ImageNet with a resulting 33 and 43,168 citations on Google Scholar, respectively, and the former is also not hand annotated. Due to these factors, this study will be focused on using pre-trained models for transfer learning from ImageNet English words to MMID Arabic words.

## Study objectives

Learners of new languages are often advised to use flashcards that have an image of an object on one side and the word on the other [31]. Two types of image recognition from a given image are the multi-label and multi-class classification problems. For the specific purpose of learning new languages, a multi-class algorithm will be of more benefit than a multi-label algorithm as each image will be associated with only a single text. With the Arabic dataset being relatively large, big data tools and techniques will be used and the resulting model will be deployed as an interactive user-friendly application.

# RESULTS

## Programming environment

Python 3.9.12 was used for data exploration and deep learning. Given the size of the data, PySpark 3.3.0 was used. Other relevant packages are TensorFlow 2.10.0, Pandas 1.5.0, Numpy 1.23.3 and Matplotlib 3.6.0. An interactive Python application was created using Visual Studio Code as an IDE, and the Dash 2.6.2 and Plotly 5.10.0 packages.

## Image selection

The MMID datasets consist of 100 images per word per language. Downloading the entire dataset will be time and storage consuming. Therefore, the Amazon Web Services (AWS) CLI v2 was used to browse through the dataset as stored in a Simple Storage Service (S3) bucket. Specifically, only the ‘scale-arabic-package.tgz’ file with a size of about 16 GiB was downloaded. Upon extraction, the entire dataset size was about 20 GiB, which precluded loading it into memory at once unless a high-specification machine is available.

## Exploratory data analysis

Images from public sources can be expected to vary in their dimensions, quality, colour (black-and-white, grayscale or full colour). In contrast, CNN models can only accept one input size. This restriction becomes even more critical when using pre-trained models, which often work with square images. Exploratory data analysis (EDA) was performed to understand the distribution of image dimensions, as well as to ensure consistency in data folder structure and readability of images for downstream purposes.

A picture containing logo

Description automatically generated

Fig. 2. A sample of images present in the MMID Arabic dataset. Each panel has been labelled with the Arabic word, which can be literally translated to ‘circles’, ‘the cloud’, ‘annual’, ‘style’ or ‘type’, ‘and the North’, ‘in Latin’, ‘ar-Rusafi’ (an Iraqi poet), ‘food’ and ‘books’ (left to right, top to bottom). Note that the ‘in Latin’ panel shows an image of Roman and Hindu-Arabic numerals.

A cursory EDA (Fig. 2) shows the presence of a mixture of image types, including illustrations, text-like images, and photographs. Moreover, several folders referring to symbols were found as shown in Table I. As stated earlier, the Arabic language, especially the written form, can be complex. Table II shows how the addition of vowels and diacritics can alter the meaning of the root word ‘ab’ (father). Coupled with borrowed non-Arabic words, such as ABBA (the Swedish pop-rock group), the complexity increases even further. In the first panel, the words ‘ab’ and ‘ibb’ share the exact same letter but each has a diacritic ‘fathah’ and ‘kasrah’ representing the English-equivalnet vowels ‘a’ and ‘i'. In addition, the word ‘ibb’ also has a ‘shadda’, which places stress on the second letter. Relatively minor modifications to the root word can also alter the meaning from a generic ‘father’ to a specific ‘to father’ and ‘his father’ as shown in the second and bottom panels. Incidentally, there is also a subtle bias towards Arabic-looking male images.

Together, these image subsets provide a glimpse into the complexity of using deep learning for natural language processing and image processing tasks, particularly when no context is given to a data scientist who will be training a model.

|  |  |
| --- | --- |
| **Symbol** | **Example images** |
| $ | A picture containing text, clipart  Description automatically generatedA golden trophy with a white background  Description automatically generated with low confidenceA picture containing diagram  Description automatically generated |
| + | Icon  Description automatically generatedIcon  Description automatically generated |
| = | Graphical user interface  Description automatically generatedTable  Description automatically generatedText  Description automatically generated with medium confidenceGraphical user interface, application, table  Description automatically generated |
| ᵒ | Qr code  Description automatically generatedA picture containing tool, brush  Description automatically generated |

TABLE I

EXAMPLE IMAGES THAT ARE LABELLED AS SYMBOLS INSTEAD OF WORDS.

The sample images discussed so far clearly have different dimension, albeit mostly square-like. To quantitatively understand dimension distribution, PySpark can be used together with simple Python wrapper functions to create a list of image heights and widths (refer to Section XX in the companion Jupyter notebook). This list can then be used to obtain a graphical representation of image dimensions.

As shown in Fig. 3 and Fig. 4, there are heavy tail distributions for both image heights and widths. About X % of images have size of xxx 🡪 see table in the main notebook

<< transfer code from image\_diemsnion\_distribution to the main notebook 00\_preprocess >>

|  |  |
| --- | --- |
| **Word** | **Sample pictures** |
| Labelled: أب  Noun: father (‘ab’)  Could also refer to a proper noun: إِبّ (‘ibb’, a Yemeni city) | A picture containing outdoor, grass, nature, mountain  Description automatically generated A close-up of some water  Description automatically generated with medium confidenceA picture containing mountain, sky, outdoor, nature  Description automatically generatedA black and white drawing of two people  Description automatically generated with low confidenceA picture containing mountain, nature, outdoor, ravine  Description automatically generated |
| Labelled: أبا  Verb: to father (‘a-baa’)  Accusative: ‘father of’  Could also refer to a proper noun: أبّأ (‘ab-ba’, the Swedish pop-rock group ABBA) | A group of people posing for a photo  Description automatically generated A picture containing person, sky, person, outdoor  Description automatically generated A person and person posing for a picture  Description automatically generated with medium confidenceA group of people posing for a photo  Description automatically generated  Table II  A person wearing a head scarf  Description automatically generated with medium confidence |
| Labelled: أباه ()  Genitive noun: his father (‘a-baa-hu’) | A picture containing text, indoor  Description automatically generatedA person in a suit and tie  Description automatically generated with medium confidenceA person sleeping with a baby  Description automatically generated with medium confidenceA person wearing glasses  Description automatically generated with low confidenceA picture containing text  Description automatically generated |

*TABLE II*

A sample of similar words in Arabic with different labels present in the MMID Arabic dataset. Potentially offensive images have been not included.

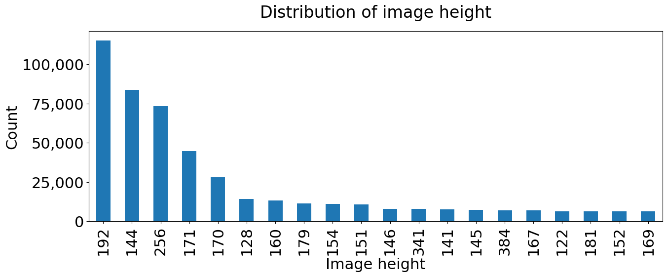


Fig. 3. XXX

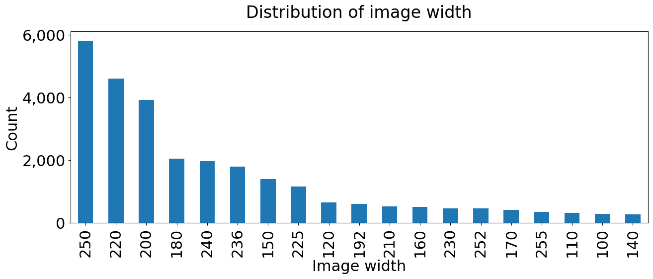


Fig. 4. YYYY

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2. This is a table footnote.

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##### Acknowledgments

The author is grateful for the provision of MMID dataset by Amazon Web Services for no charge.

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