An Image Recognition System of Aboriginal Artefact for Knowledge Sharing using Machine Learning

Yajun Ma[1], Asif Karim[†1] and A S M Farhan Al Haque[2]

[1]College of Engineering, IT & Environment,Charles Darwin University, NT, Australia
[2]Deparment of Electronic Systems, Aalborg University, Copenhagen, Denmark

Abstract

Acquiring knowledge about indigenous artefacts is difficult without prior experience. Due to the scarcity of digitally preserved artefacts, the new online generations are not exposed to even the most basic concepts. This paper demonstrates the feasibility of Image recognition technology for providing an app to describe aboriginal artefacts. By using Microsoft Custom Vision Service to classify and train the data, the predictive API of the model is called from a progressive web app developed to take photos of artefacts and retrieve their classification and description. We have divided aboriginal artefacts into the categories of tools or paintings for detection and description by machine learning systems. We test the trained model by taking new photos of artefacts already known to the system with the app camera. This performance was tested and compared with human classification to determine its usability. The results of the testing of our app show that the identification of aboriginal artefacts is applicable in certain cases.

CCS Concepts

• ***Applied Computing*** $\rightarrow$ *Computers in other domains; Digital libraries and archives;*

1. Introduction

At a seminar on Indigenous Knowledge held in Darwin, the capital of Northern Australia, several women from the local Larrakia Indigenous community advocated storing their elders' knowledge in a database to preserve some of their knowledge before the death of the elderly [Chr04]. This suggests there is a gap in the application of IT technology for the requirements of Indigenous Knowledge storing and sharing. Until 2021, Researchers Jarrad Kowlessar and his team from Flinders University used machine learning to analyze images of rock art collected during surveys in Marrku country, Northern Australia [SU21]. This was the first time Machine Learning was applied to analyzing Aboriginal rock paintings. They tried to use this approach to show how the rock art in the Wilton River relates to others in other parts of Arnhem Land. Although how to collect data is a topic that the Australian government is studying at present [Bid14], how to accurately express the knowledge of Indigenous people, especially about their artefacts to their descendants and other people, has been little studied.

It is vital that Indigenous people not be excluded from using computer and Internet technologies to acquire and share knowledge [KH09]. When we deal with Aboriginal data, its structure, search process and interface, ownership and right to use must also reflect and support the way Indigenous people exist and understand, as well as their control over their knowledge [Agr95]. In addition, when it comes to Aboriginal knowledge, it should be considered as four themes: control, protection, recognition, and respect, and it is required to obtain consent before using indigenous knowledge to help avoid causing cultural harm or offence [Tra21].

The Aboriginal artefact as a part of Indigenous knowledge has a long history. Symbols and shapes in the artefacts are used to chronicle and convey knowledge about the land, events, and of course, beliefs. This becomes another method for writing down peoples' stories, teaching survival and use of the land. Each symbol and shape have its special meaning and function.

This study is mainly for researchers and agencies who are looking for effective machine-learning based digitization and preservation of Aboriginal knowledge expressed through a range of artefacts and paintings.

2. Approach

To fill the above discussed gap in relation to digitization of indigenous culture through machine learning based image processing, this research developed a principle of Progressive Web Application (PWA) web and mobile application based on an image recognition technology platform. This provides a case study with which to investigate the application of Aboriginal knowledge sharing.

† Corresponding: asif.karim@cdu.edu.au

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To develop the background recognition module, we compared two different ways (Tensorflow + Keras and Azure Custom Vision) for convenience and usability. The implementation of the front-end referred to the principle of PWA. After that, the application was tested to verify its practicability in practice.

The specific input of the training model is a series of photos taken from existing Indigenous artefacts in NT Museum. The performance test of this application evaluates the link speed, page access speed and system construction speed of the application. We also considered the data privacy and security of the system, which is important in cultural. They are intensifying their commitment to take actions to protect personal data from unauthorized persons or improper access. In addition, the transmission protocol between PWA and back-platform Django would be HTTPS, which means data is transmitted using TLS (SSL) to encrypt typical HTTP requests and responses. Therefore, security was ensured.

3. Experiments

The task of image recognition is to create a neural network that is adapted to process the pixels in the recorded image. The image sample data is labelled and input into the network so that the computer can learn how to recognize similar images.

3.1. Using TensorFlow + Keras

We have used Keras for deploying the deep learning model. When we run the program, we encounter many packages that are not compatible with the current Python version. For example, Tensorflow 1.14 requires Python3.7, while Python 3.8 corresponds to Tensorflow 2. Versions are updated frequently and are not fully Backward Compatible. Because the initial training data set exceeded the load that the author's computer could calculate, the author had to reduce the data set and ended up with an 81% absolute average accuracy. In the operation process, the image recognition was not completed due to limitations of device resources, so we had to reduce some images.

We used different sizes of datasets (40 images, 60 images and 80 images) as input, and recorded the accuracy of each size data set. To further compare the accuracy of the model, the Accuracy, Precision and Recall indexes were introduced for evaluation. The equations are [Pow20]:

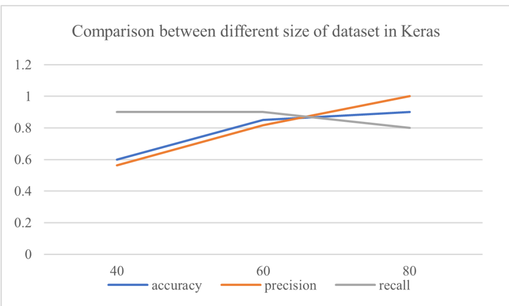

Figure 1: *Comparison between the different sizes of the dataset in Keras*

3.2. Attempt using Azure Custom Vision

The Computer Vision service provided by Azure cognitive services is packaged into APIs, and it can generate, deploy and improve our own image classifiers. The Custom Vision is based on the convolutional neural network we mentioned above [Pej19]. We use the same data set for training, and the comparison results are shown in Figure 2.

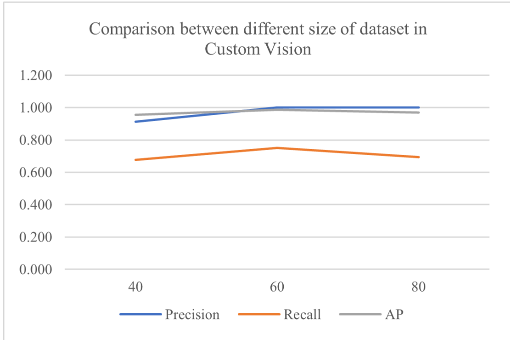

Figure 2: *Comparison between the different sizes of the dataset in Custom Vision*

3.3. Comparison of the two

Customer Vision showed higher precision, especially in precision, more analysis will be in the Analysis below. In comparing the two different methods, we found their respective advantages and disadvantages.

1. **For Tensorflow + Keras**
   - We have full control over our network and how to train it, and we can completely embed the model into our code and run it locally.
   - We need to deploy our own model, which will be a complex project, and the update speed of related technologies is fast, so we need to constantly debug. In addition, we also need to manage data effectively by ourselves.
2. **For Computer Vision**
   - This includes a complete turnkey for a rest API deployed in the cloud, and some labeling tools are also provided for us to add pictures and label them.
   - We have no control over the learning algorithm and it is difficult to run your model locally and completely for free.

To consider the usability or the feasibility of Custom Vision in image recognition we had to realize the front-end to the API for the user to access the model.

4. Implementation

The mobile web application to test the idea for image recognition from photos of artefacts was implemented as an Ionic app and stored on Firebase `https://isaboriginal.web.app`.

According to the concept of the research question, combined with the requirements of the actual application scenarios, the system needs to complete the whole process of artefacts recognition from the perspectives of the client and the server, such as user query, image understanding, result image corresponding text query and query result push to the client, add the content and other task processes. Figure 3 demonstrates the user-case process and the service request flow is shown in Figure 4. The system includes two parts: back-platform and front-platform. The back-platform is developed by the Python Django, and it is responsible for receiving and returning Aboriginal artefacts information and maintaining the dataset, and the front-platform is responsible for photographing and information display which is based on PWA (progressive web application).

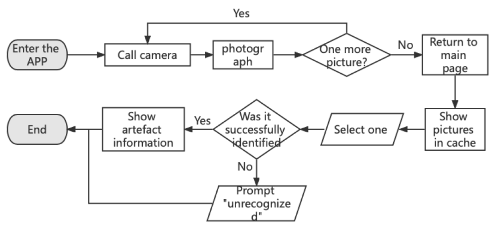

Figure 3: *Flow Chart to demonstrate user case process.*

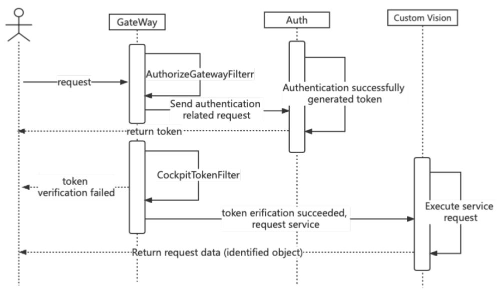

Figure 4: *Service request UML.*

4.1. Front-platform

PWA technology enables the web to remove the browser from applications. Using PWA technology, our web app can be installed on the desktop, have its own fixed entry, and can call many system functions to realize the experience of native applications. With patches this feature has significantly improved in three aspects: security, performance and experience.

4.2. Back-platform (Django)

The front-platform takes photos and uploads the photos to our Django back-platform. The pictures are then uploaded to the Azure Custom Vision service. Next we will receive the data returned from Custom Vision. The data will present two fields: tgName and tgId, tgName refers to the artefact's name. The Django site will send a request to the database based on tgName, and the development server will return the artefact's name along with the rest information set in the back-platform. Then the PWA will get the artefact's whole information from our Django side.

5. TESTING COMBINED SYSTEM

There are two performance metrics Precision and Recall in each iterated model. If we want to identify accurate test samples, we need to pay attention to the Precision, and if we want to identify all samples, we need to pay attention to the latter. Due to the limitation on the number of images we uploaded and the instability of data features we collected, the precision rate of each classification training is not stable enough, as well as the recall rate.

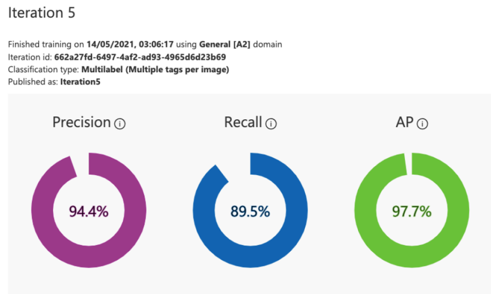

Figure 5: *Workspace of Custom Vision for tagging categories.*

5.1. PWA Performance testing

The system would execute all the test cases from the client through a black-box test. The performance test of this system evaluates the performance of the system by testing the speed of the first opening, the speed of page access and the speed of system construction.

We compared the performance difference between using ServiceWorker (the programmable network proxy for PWA) [Goo20] and not using SW. Focused on the home page, we first use the service worker technology to optimize the network processing, cache the commonly used CSS, JS and image resources, and significantly improve the display speed of the app window. The network response time from the response start is significantly reduced using SW and the test also showed that the page loading time is stable after using service worker, the network fluctuation has little impact on page loading (see Figure 6), which will significantly improve the user's actual experience.

5.2. Custom Vision API validation test

We tested a real artefact from the Australia Library and Museum and Art Gallery of the Northern Territory using our APP (we have tagged in the Custom Vision model). After a short time, the result showed that the probability is 0.7601098 for this artefact, which is consistent with our manual categorisation. Figure 6 shows that the application can display the correct information of the Aboriginal artefact.

We changed the camera angle of the tested object. The result shows that the probability of the object can still be accurately identified after the original object is slightly adjusted.

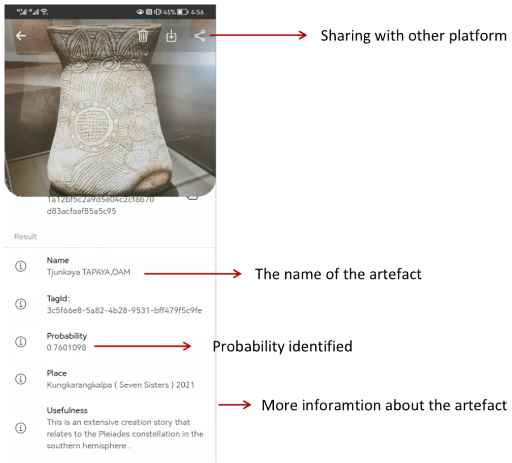

Figure 6: *The result of the recognition.*

6. Analysis

In the process of model building, Custom Vision uses the way of cross-validation to improve the recognition. Custom Vision holds different iterations, which are different models trained each time. Machine learning needs constant training to become more accurate as we gather more resources. So, we train the model regularly in the process of using it. However, not every training can achieve results better than the last one, as adding a new tag or adding a new image with more noise may affect the results. So the principle of iteration we experimented with is: If the second training result is better than the first, we can use Iteration 2 directly in production, if not, we retain Iteration 1. The percentages of the two metrics (Precision and Recall) have different effects in different scenarios, so they are a trade-off between each other. Fortunately, these two values can be adjusted through the probability threshold provided by Custom Vision according to different scenarios. When we use a higher probability threshold, there tends to be a higher precision and a lower recall. A lower probability threshold does the opposite. As the number of training sets increases, we need to improve recall at the expense of precision. But the probability threshold stays around 50% usually.

It is important to note that the physical features of the object should be clear. It is necessary to consider the scene when users take photos, and try to use on-site photos for training. Even large high-definition images can capture more image features. However, when users use images with various noise levels for prediction, they may not be accurate enough. So, the training set should be based on real artefacts.

Infusion of additional data to the training run will provide a more varied pool of artefact types and improve the ability to categorise more artefacts. This process is slow and requires a detailed description of each artefact. What is significant is the fact that when combining the image modelling tool with a simple user interface, we have achieved an app for users to photo and analyse any artefact, limited by the pool of artefact types collected.

By developing this image recognition application for indigenous artefacts, we find that the Custom Vision-based method can provide accurate classification of images that improve on human image recognition where they are not familiar with the artefacts. The use of a PWA shows the advantages in user experience available in client application development. Therefore, the advantages of both can be combined to provide a simple application of Indigenous artefact recognition.

7. Conclusion

Compared with the traditional way of building neural network model with Keras and Tensorflow, Azure Custom Vision has the advantage of simplicity and quickness, allowing individuals or small groups to quickly build image recognition classifiers. At the same time, with the help of PWA to develop mobile applications with a better user experience, which will improve people's cognitive efficiency of Indigenous artefacts, to quickly acquire and share Indigenous knowledge. The idea of developing Indigenous images recognition application is to improve the efficiency of access to Indigenous knowledge in the real world. This can be achieved quickly with Azure Custom Vision and PWA. Such an automated ML-based application will be able to effectively and quickly classify the cultural context and value of the object. The obtained information can then be used to compile a valuable dataset of aboriginal knowledge which will be of immense value to relevant researchers. The proposed framework can also be used for indigenous knowledge sharing and preservation in other parts of the world.

8. Acknowledgement

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