Pokémon Compendium: A Machine Learning-Based Setup Which Detects Pokémon from Images

Abstract

Plenty of image recognition programs exist, but very few of them are dedicated solely to Pokémon (refer to the appendix to know what Pokémon is). In addition to online Pokémon directories (called the Pokédexes), many of them do not include image recognition. The goal of our research is to combine image recognition with our Pokémon directory to create a new type of catalog with machine learning. Our paper introduces an empirical comparative investigation into the capability of some familiar machine learning algorithms, including convolutional neural networks, transfer learning with pretrained models, support vector machines and k-nearest neighbors classification, in the context of identifying the Pokémon in a user-uploaded Pokémon image. Not only does this research provide the name of the Pokémon, but it also provides the statistics for the Pokémon. The performance of the four algorithms is compared over two metrics: accuracy and execution time. The accuracy of our Transfer Learning with Pretrained Models algorithm turned out to be 90.6 percent which was the best among all the models. It is worth mentioning that Convolutional Neural Networks followed close on its heels with an accuracy of 90.2 percent.

Introduction

Briefly Introducing Object Detection and Image Classification, and Delineating the Need for the Most Accurate Object Detection Algorithm

Object detection involves differentiating and identifying two or more objects in the same image. Image classification is a special case of object detection where an image with one object is classified. Industries like robotics and automation, the fields of medicine, biological sciences, education and learning, business and information technology, law, social media, and many others are deeply dependent on machine learning [1, 2]. With an overabundance of image datasets on the internet, the need for comparative analyses of machine learning algorithms has arisen in recent years. This is particularly important because in the present age of data flareup, before analytics is embarked upon, we must know which algorithm is the most appropriate one to be applied to one of the disparate image types and datasets. This forms the basis of our research.

Pokémon Image Recognition

Our research aims to draw comparisons between the accuracy of four machine learning algorithms to classify any of the first six generations of 721 Pokémon from their images. The algorithms we employed are Convolutional Neural Networks, Pre-Trained Models, Support Vector Machines, and K-Nearest Neighbor classification. By employing a dataset of Pokémon images as a common underlying thread for the estimation of the same metrics across all the algorithms, the respective performances of the models, which are all built upon unique architectures, have been rendered analogous to each other. The conclusions that have been reached by evaluating the efficiency of each implementation have led to the gain of insight into the distinctive aspects of each algorithm while determining which model performed the best in recognizing the images of Pokémon.

Our research comes with a website where a user may upload a Pokémon image, choose the algorithm of their choice, and demand to know what Pokémon the uploaded image contains. The interactive website uses the chosen algorithm, runs it over the image, and outputs the name and attributes of the predicted Pokémon and the accuracy with which the prediction was made. Thus, it is a Pokédex (an index of Pokémon data) of the first six generations of Pokémon. An additional feature of our Pokédex is that it is, as we write this report, the most comprehensive machine-learning based Pokédex available when it is deployed.

The combined number of images that were used to train the algorithms is more than ten thousand. We drew those images from various sources across the internet and ensured that all those images were open source and freely available, even if rendered by individual artists. Also, we do not claim ownership of those images. All we did was use the images to train our machine-learning models. This prevented any copyright infringement issues.

Related Work

Much work has been done in the field of object recognition using machine learning algorithms, specifically neural networks, and soft computing techniques. However, Pokemon Image Recognition seems to be a rather untouched area.

A user who goes by the handle Code AI gives a step-by-step description of how they used CNN for Pokémon image recognition [3]. They have used Vishal Subbiah's Pokémon Image Dataset from Kaggle [4]. Chirra et al, in their recent research paper have used transfer learning to classify Pokémon images [5]. They have created an index of Pokémon which they term Pokepedia. Their ResNet101 pre-trained model gave the best accuracy when measured against the rest of their models [5].

Chu *et al*. presented their work 'Attribute Prediction in Pokémon Images using CNNs' at the 2nd International Conference on Electrical Engineering, Big Data and Algorithms (EEBDA) in China [6]. Their algorithm can determine the number of Pokémon belonging to a specific type (fire, water, grass, bug etc.) in their dataset consisting of images of 802 Pokémon. They utilized the images of the Pokémon obtained from a scorching game branded as Pokémon as their dataset [6]. They crafted a CNN algorithm harnessed it for type classification from the images in their dataset before they enhanced (preprocessed) their data (Pokémon images) and ran another iteration of CNN on it to improve their results [6]. However, their algorithm cannot determine any other statistic of a Pokémon, including the generation or even the name. This gives it serious limitations compared to the work that we propose.

There are a few different implementations of image detection that are currently available to be used by the public. The most common app that's used is Google Images. The Google Images website takes a user's image and rapidly comes up with the identification of the object that the user is attempting to identify. Many other search engines, such as Bing and Yahoo, have created similar algorithms.

What makes this research different is that it's directly related to identifying Pokémon. A search engine will identify the Pokémon, but all that the search engine will do is link someone who queries to websites that contain the information about the identified Pokémon. This research not only identifies the Pokémon but provides the statistics of the Pokémon. It's intended to be more user-friendly and that users don't have to rely on other websites for the information.

Another related work is the use of online Pokémon directories (commonly referred to as a Pokédex). What makes this research different from a Pokédex is that it can give all information about a Pokémon based solely on the image of the Pokémon uploaded to it. It will detect the Pokémon in the image and provide information about it

Proposed Work

The fact that no popular machine learning based model exists for Pokémon image classification formed our motivation. In this regard our hypothesis was that machine learning algorithms will help us classify and predict Pokémon based on image input. We also hypothesized that CNNs would have the best accuracy among all the models.

The main objectives of our project include the identification of the first six generations of Pokémon (containing 721 Pokémon) with image recognition and to detect from more than one different "style" of Pokémon images, including screenshots from video games, from artwork of individual artists and studios, from TV shows and from card portraits. Our models are trained only on 721 Pokémon because we needed a certain minimum number of images for each Pokémon so that our algorithms can train adequately, and there was a limited availability of images of Pokémon beyond the sixth generation (refer to the appendix).

Therefore, our project is not intended to be an alternative to a modern Pokédex, which contains data of many more Pokémon than ours. Rather, it is meant to be a tool that is used for people who may not recognize a Pokémon, or who might want to look up the stats of a Pokémon based on an image. That said, as we write the report, our Pokémon directory is the largest machine learning-based Pokémon index. We would prefer to call it Pokémondium, a portmanteau for 'Pokémon compendium'.

A variety of Pokémon image datasets are available to evaluate the performance of different algorithms. Some orthodox Pokémon image datasets for assessing the performance of machine learning algorithms are Kvpratama's Pokémon Images Dataset containing 819 Pokémon images with a compressed total size of size 74 MB [7] and Rohan Asokan's The Complete Pokémon Images Dataset, which is a collection of 898 images of all the Pokémons taken from the Pokedex database with a compressed total size of 117 MB [8]. Both the datasets are accessible on Kaggle. However, since our aim was to create a more comprehensive catalogue of the first six generations of Pokémon, we created our own dataset for this study consisting of 10,073 images.

The information that's provided as the output once the algorithm is provided with the image includes the name of the Pokémon that it identifies as well as its stats, type, and generation. The only prompt that it takes is an image, so the web interface is simple and user-friendly. The stats include the ID index, the gender, the height, the weight, and other attributes of the Pokémon. If the user finds a Pokémon image on the internet and wishes to know more about it, the user will only have to click a picture of the image using his or her smartphone and upload it to our program using the UI. They may also download the picture and upload it directly to the appropriate input field in the UI we propose to create and have almost completed. The user may also input the path of the Pokémon in his or her device or storage as a string into the algorithm instead of directly uploading an image. We have trained our models and tested them using datasets they have not encountered before. Our algorithms are also able to show the accuracy of testing and training.

Convolutional Neural Networks (CNNs)

We are using CNN for image classification because it is highly efficient at recognizing specific patterns from the images, and it tends to have the highest accuracy when it comes to image classification. It also focuses on color recognition and different color planes, so it tracks very critical features on each image to produce a very accurate prediction. CNN is, therefore, the best suited machine learning algorithm for image classification. We have used the InceptionResNetV2 CNN algorithm, which is built in the Keras package within the TensorFlow library of Python.

Inception-ResNet-V2 is a convolutional neural architecture which uses the Inception family of architectures integrating Inception with residual connections. It is described as a very deep architecture that combines elements from both Inception architecture, created by Google, and Residual Networks, shortened to ResNet. This architecture was developed with an aim to enhance algorithmic performance by leveraging residual connections in conjunction with the Inception modules [9].

The key components of InceptionResNetV2 include:

1. Inception modules, which consist of multiple parallel convolutional pathways of different kernel sizes (1x1, 3x3, 5x5, etc.) and pooling operations. These modules enable the model to learn the features of images at multiple scales.

2. Residual connections: Borrowing the best features of the ResNet architecture, InceptionResNetV2 includes residual connections which are also referred to as skip connections. These connections allow the flow of information through the network by adding shortcuts that bypass some layers, which in turn helps in relieving the vanishing gradient problem, facilitating the training of deep neural networks.

3. Stem layers: The beginning layers of the network, which are named stem layers, are involved in processing input images, and extracting basic features. These layers consist of convolutional, pooling, and normalization operations. They are common to all CNNs, including InceptionResNetV2.

4. Reduction blocks: Interspersed within the architecture are reduction blocks that reduce the spatial dimensions of the feature maps, helping to decrease computational burden while retaining important information. They use pooling.

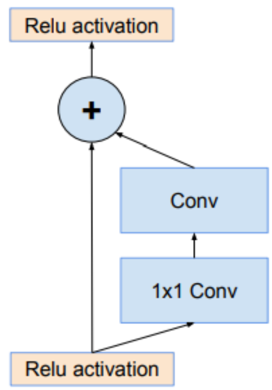


Fig 1. Simplified version of a ResNet connection [9, 10]

Conv2D (Convolutional 2D) is a specific type of layer used for processing 2-dimensional spatial data, most prominently, images. Conv2D layers apply convolutional operations to input data to extract various features through learned filters or kernels. They are the stem layers in a CNN. InceptionResNetV2 incorporates various types of layers, including Conv2D layers.

Pretrained Models with Transfer Learning

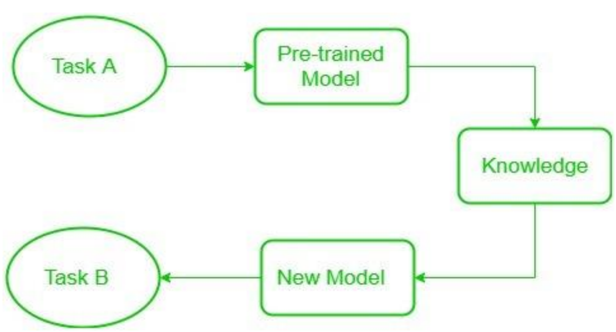


Fig 2 [11]: Transfer Learning block diagram

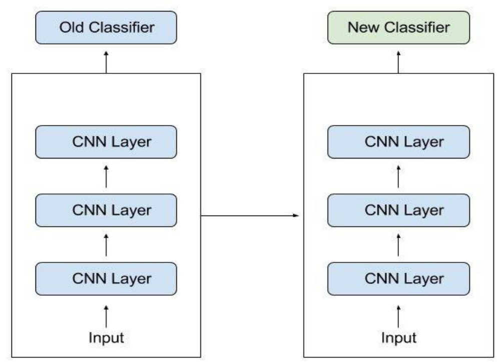


Fig 3 [12]: Transfer learning where the pretrained model as well as the new classifier are based on CNNs

Transfer Learning can be done in two ways:

1. Extending the pretrained model: This is used by our InceptionResNetV2 model. Extending a pretrained model involves adding new layers on the top of the existing pre-trained model, keeping the pre-trained layers frozen (not trainable). The added layers are used for task-specific classification. The pre-trained layers act as feature extractors, capturing generic patterns and high-level features from the original dataset they were trained on (e.g., ImageNet, on which InceptionResNetV2 is trained).

The additional layers learn to interpret the high-level features extracted by the pre-trained layers and adapt them for the specific nuances of the new dataset. These new layers are trained from scratch.

2. Adjusting the pretrained model (Fine-tuning): This is also termed fine-tuning. It involves unfreezing and modification of the topmost layers of the pretrained model, also termed the old classifier. Some existing layers in the pre-trained model are unfrozen, allowing them to be further trained (fine-tuned) on the new dataset while also adding new layers on top. Fine-tuning is defined as updation of weights of both the newly added layers and selected layers from the pre-trained model. This allows the network to adapt not only to the new task but also to adjust some of its previously learned representations to better suit the new data.

Support Vector Machines (SVMs)

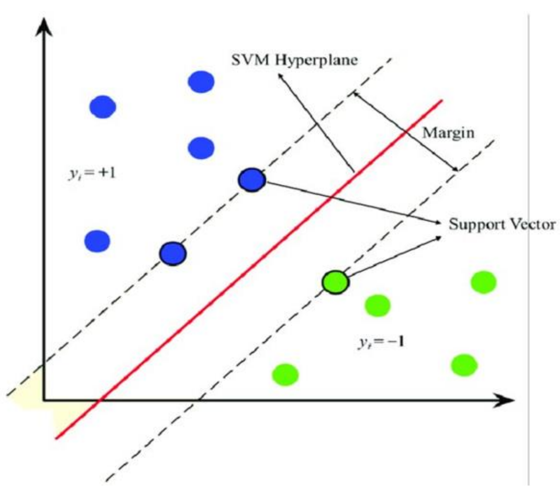


Fig 4 [13]: The diagrammatic representation of a linear SVM Classifier that separates the two classes. SVMs aim to find the optimal hyperplane to separate different classes while maximizing the margin between the closest data points (support vectors).

K-Nearest Neighbors

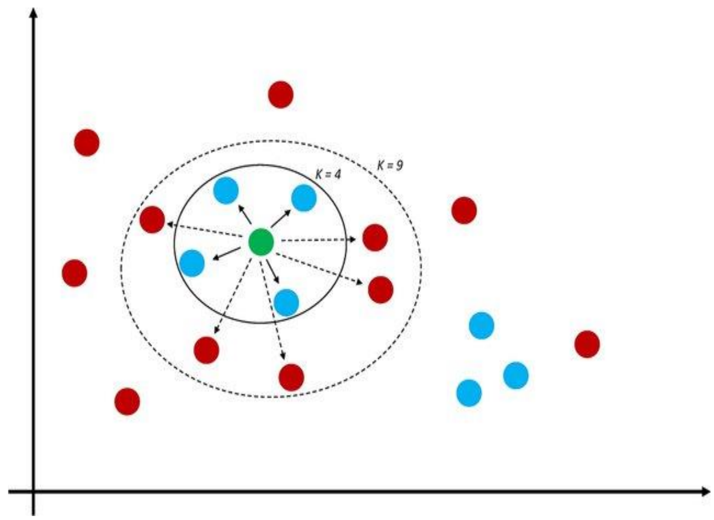


Fig 5 [14] A mathematical illustration of K-NN

An instance of the k-nearest neighbor machine is shown in the above figure [14].

1. The classes are catalogued based on their feature values.
2. The classification of a member belonging to one of the classes is determined by a majority vote in the member's neighborhood.
3. The number k is the number of neighbors that will be used to classify the member. They are the ones that most closely resemble the member to be classified.
4. The choice of k is crucial to classification. For example, if it is needed to classify the green member based on $k = 3$, the member would be placed alongside the blue members. If

k = 9 is chosen, the member would be placed alongside the red members.

Experimental Evaluation

As of writing this paper, we currently have an active, working implementation of three of the four algorithms. We will be evaluating the performance of the following algorithms: K-Nearest Neighbor, Convolutional Neural Networks, and Pre-Trained Models.

Hardware

We (the authors of this report) have been running our programs on three different machines. However, it's important to note that the figures below will involve tests being run on one author's computer, which is Eric Nieters' hardware. Listed below is a table of hardware that has been used to conduct this research.

	Eric	**Ibrahim**	**Raj**
GPU	NVIDIA GeForce RTX 4070 Mobile	8-Core Integrated GPU	Intel HD Graphics 620
CPU	i7-13620H (16 Ghz)	Apple M1 Chip	Intel Core i7-7600U
Cores	7 Cores	8 Cores	Dual Core
RAM	64GB	8GB	8GB
Storage	3TB SSD	256GB SSD	256GB SSD

Table 1. Hardware specifications

Dataset

The dataset for this research consists of 10,073 images of 721 Pokémon. Originally upon training these models, there were about 5,400 images for the 721 Pokémon. There were many accuracy errors, especially with the CNN algorithm, where Pokémon were being inaccurately predicted.

The original collection of data consisted of using a library called "bing-image-downloader", which takes a string query and a set number of images to download. At first, the original parameters were the name of the Pokémon, then 10 images of each of them. This collected roughly 7,210 images, which were then filtered out by hand to ensure that some data was removed that was deemed poor for machine learning. Some examples consist of the following: Images of Pokémon that contain props, clothing, watermarks/words, complex backgrounds, or incorrect results. An example of an incorrect result was the Pokémon called a "Durant", which the bing-image-downloader library gathered results of Kevin Durant, a basketball player.

Once the data was collected, all Pokémon had no less than five images to train from. There were roughly 5,500 images that were deemed fair for machine learning. However, with the issue mentioned earlier, this was underfitting our machine learning models. To mitigate this, the dataset was recreated. Using the similar data collection method above, a total of 20 images were collected for each Pokémon. This resulted in a total of 14,420 images that were collected for the dataset. Another change that was made to the collection of data was using the query "X pokemon png", where the X was replaced with the Pokémon that was in a spreadsheet containing the names of all the Pokémon. This spreadsheet has been created by

Alopez247 on Kaggle. This dataset is used by our Pokémondium for displaying all the statistics for each Pokémon once it has been identified.

Continuing with the dataset reconstruction, approximately 4,300 images were filtered out from the dataset leaving a total of 10,073 images across the 721 Pokémon. The reason why a .png file was included in the search query was to filter out any potential backgrounds that the library may have picked up. A background to an image was possibly going to alter the performance of the training algorithms that the scripts were going to use. Specifically with K-Nearest Neighbor, which will be explained in a future subsection.

Learning Environment

The learning environment for the models we described involves supervised learning at every step and for all algorithms. It involves the images that constitute the dataset, as well as the .csv file that contains the stats of the Pokémon and which the website gathers information from to produce the output. The agent in our algorithm interacts with the images and learns from the patterns and colors of each Pokémon.

Implementation with learning parameters

1. CNNs: We used InceptionResNetV2 as our base model. As an inbuilt model, it could not be unfrozen to reveal its kernel size, strides, padding etc. But it was extended using three additional layers:
   a. The GlobalAveragePooling2D() layer, which reduced each feature map to a single value by averaging all values in the feature map, providing a fixed-size output;
   b. A fully-connected dense layer with 1024 nodes and ReLU Activation This layer performs a linear transformation on the incoming data followed by an element-wise ReLU activation. It introduced non-linearity (through ReLU) to the network and helps learn complex patterns in the data.
   c. An output dense layer with the same number of nodes or units as the number of classes (721) with softmax activation which calculated class probabilities for our multi-class classification.

   Our CNN model plateaued at ten epochs. It used a batch size of thirty-two, and a training to testing ratio of 80 to 20 percent.

2. Transfer Learning with Pretrained Models: The **`run_pretrained(user_input)`** function initializes the pre-trained CLIP-ViT-B-32 model using **`SentenceTransformer`** library. The upper layers are unfrozen and finetuned for our dataset. Ten epochs were used to gain maximum accuracy.

3. K-Nearest Neighbors: This is the algorithm which we implemented from scratch, that is, without using any machine learning libraries.
   a. Our algorithm performed best at k=4, so we used that as the value of our k.
   b. It first converts all images of Pokémon into a multidimensional array of tensors. Each tensor keeps track of the color value of each pixel in a particular image.
   c. Euclidean Distance is measured between the tensor formed from the input Pokémon image and all the tensors that represent our entire

dataset. Then the distance values are sorted.

d. The shortest three distances are returned, and based on them, the algorithm returns the name of the Pokémon in the input image, while the website fetches the rest of the stats of the pokemon.

4. Support Vector Machines: SVMs are not well-suited to image data, but work well for smaller datasets and "plottable" data. We should have discarded the algorithm in the initial phase itself and taken, in the place of it, some other algorithm like random forests, which would have begotten better results than SVM. Yet we kept SVM because we wanted to showcase its implementation as a learning opportunity for those who read this paper, so that they avoid using SVM for image recognition.

   We used transfer learning here, with CNN as our base model or old classifier. Its layers were left frozen, and SVM was appended as the new classifier. It used svm package from sklearn library, and its kernel (hyperplane) was chosen as linear.

Outcomes

To ensure there was no overfitting, the models were trained on test data and their respective accuracies were recorded. The models continued to be accurate, showing there was no overfitting. However, there was underfitting in support vector machine model and in k-nearest neighbor implementation, and the reason we found out was that both algorithms are not very well suited to image recognition.

To test our newly formed algorithms for error we built a small test set containing 46 images of six Pokémon. We built another test subset over all images of the first generation of Pokémon we had, which came to about 1700 images. This was to test the algorithm's performance over medium to large datasets. Finally, each algorithm was run on the entire dataset of 10,074 images. The following are our experiment-wise outcomes:

<u>*CNNs:*</u>

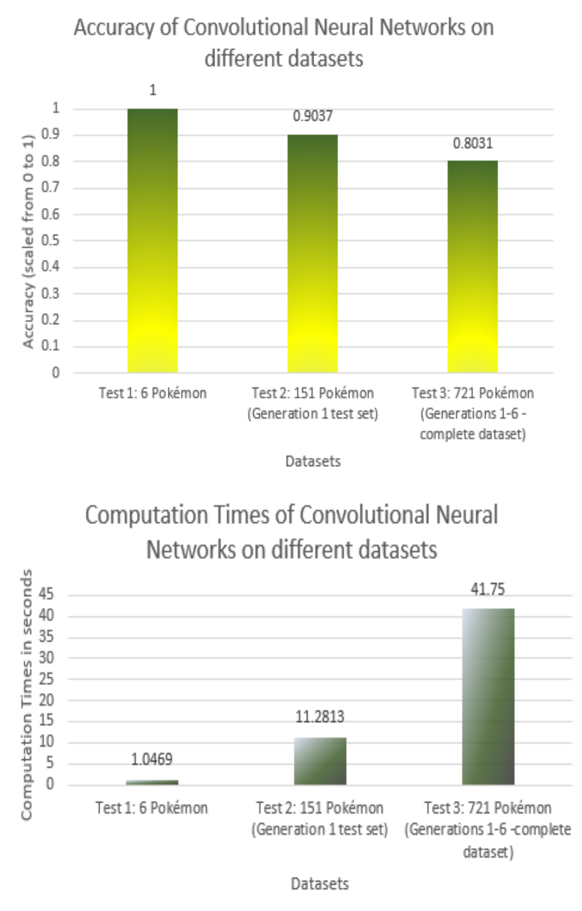


Fig 6: Accuracy and computation times of CNNs over different datasets

<u>*Transfer learning with Pretrained Models:*</u>

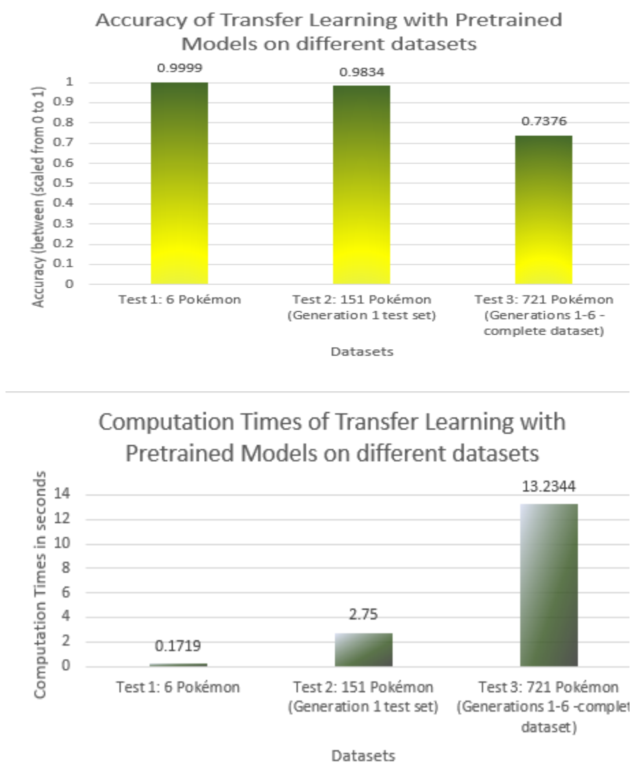
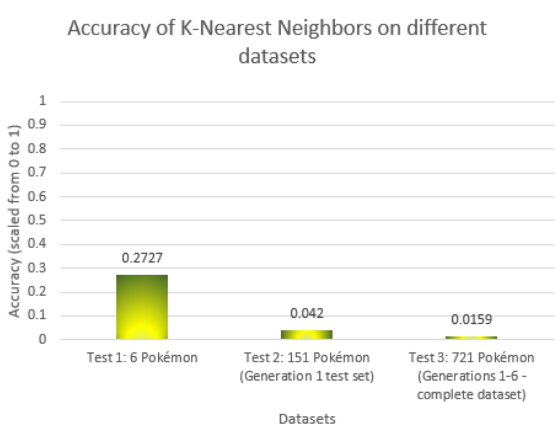


Fig 7: Accuracy and computation times of Transfer Learning over different datasets

K-Nearest Neighbors



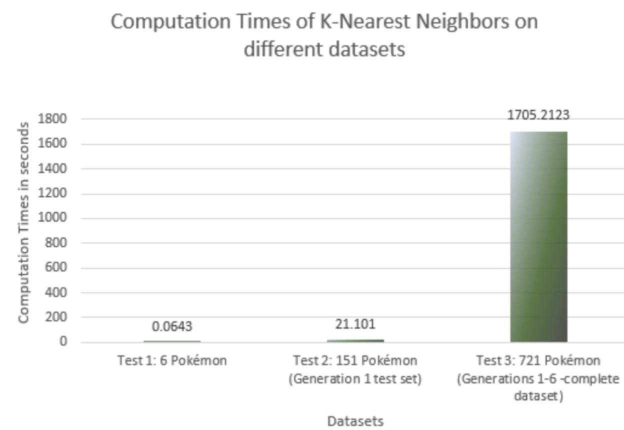
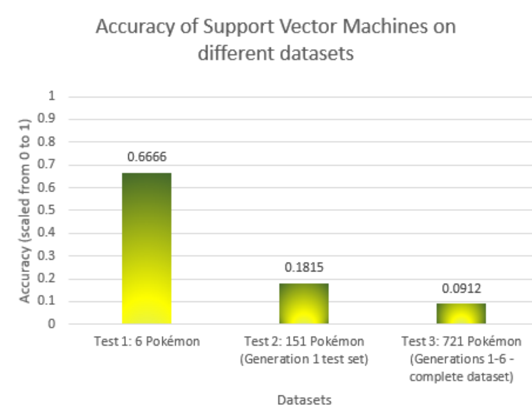


Fig 8: Accuracy and computation times of K-NN over different datasets

Support Vector Machines:



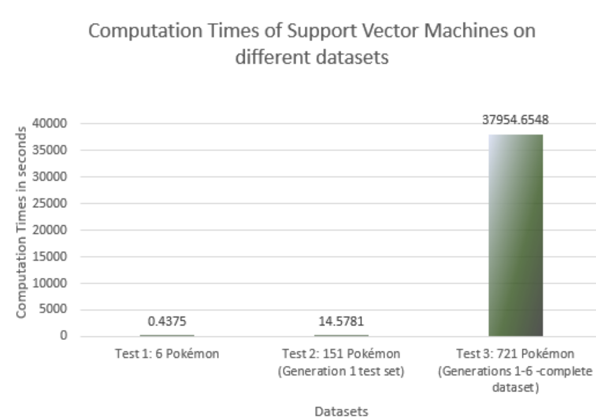


Fig 9: Accuracy and computation times of SVM over different datasets

__Relative complexity of each of our algorithms:__

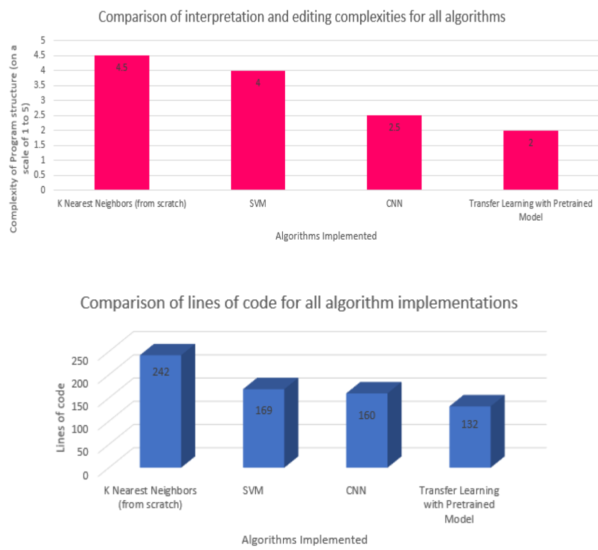


Fig 10: Relative complexity of our four algorithms

The high complexity of some of our algorithms and the injunction of implementing at least one of the models without using machine learning libraries presented roadblocks for us to implement metrics like precision, recall, F1 score and are under the Receiver Characteristics Operating curve for the models.

__Our website:__

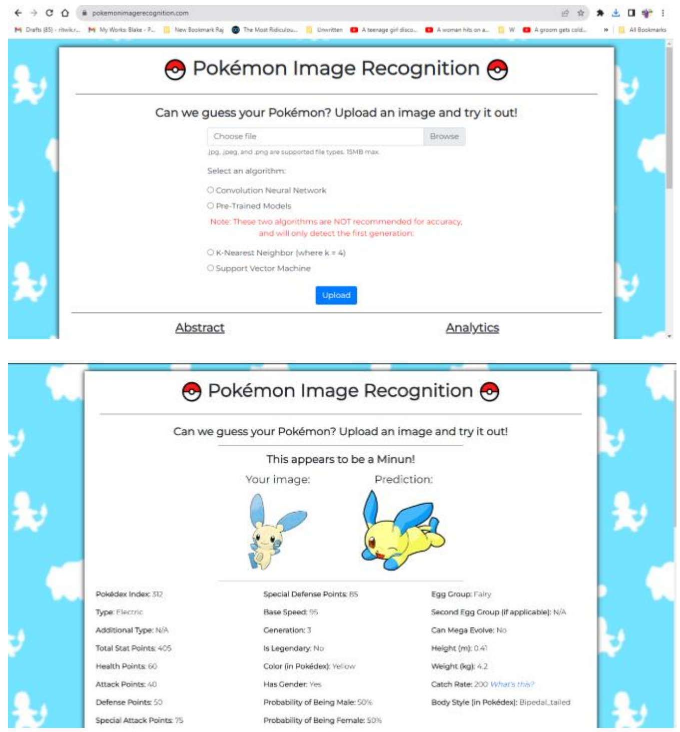
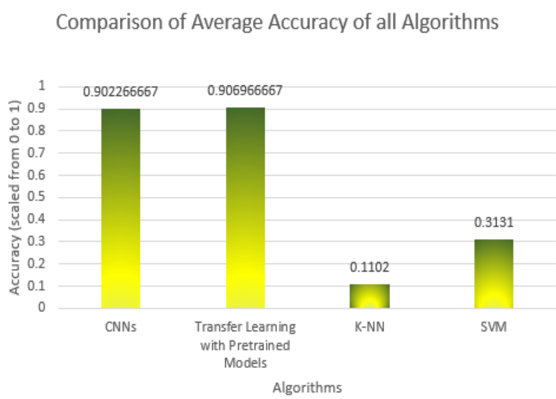


Fig 11: Screenshots from the website that hosts the Pokémondium

Our website, www.pokemonimagerecognition.com, uses PHP, HTML, CSS, JavaScript, and the Bootstrap framework in its design and implementation. It showcases the abstract of our paper and the accuracy and computation times for our algorithms, so that the user is informed beforehand as to which algorithm should be chosen to get a more accurate and timely result for the user's input image.

Conclusions



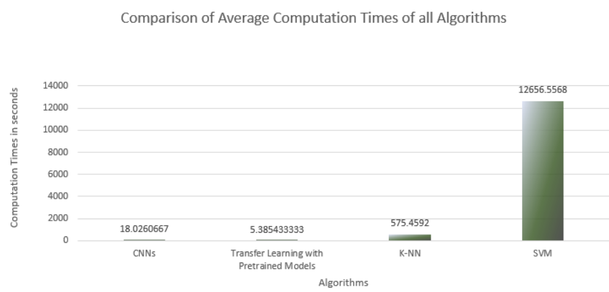


Fig 12: Accuracies and computation times for all models compared

Average accuracy and computation time, respectively, for each algorithm

1. Convolutional Neural Networks (90.2% and ~18.02 seconds)
2. Transfer Learning with Pretrained Models (90.6% and ~5.4 seconds)
3. Support Vector Machines (31.31% and ~12656.56 seconds)
4. K-Nearest Neighbor (11.02% and ~575.49 seconds)

Transfer Learning with Pretrained Models (CNN as Pretrained Model as well as New Classifier) performed the best on both metrics, computation time and accuracy. CNN's results were very similar to Transfer Learning on the metric of accuracy, but took longer computation times. SVM and K-NN took immensely long to execute as well as provided much poorer performance compared to the Transfer Learning and CNN models because they are not suited for image recognition. They are not good at processing image data, especially large tensors. Since image data has large tensors, curse of dimensionality was a problem with K-NN. The performance of SVM shows that it is much less suited to large datasets with many classes compared to the other three algorithms.

Our hypothesis that CNNs would be the best model was disproven but with a negligible margin of error, and we attribute this purely to probability. Perhaps if the algorithms are trained on the same dataset in a fresh environment, CNNs would perform better.

Future Work

1. Metrics like precision, recall, F1 score and area under the receiver operating characteristics curve may be used to better compare the performance of the machine learning algorithms we have employed.
2. The algorithms can be trained on all known Pokémon, which currently number more than a thousand.
3. Once the best algorithm(s) is/are finalized, we may use them for more widely useful tasks like medical image recognition, for example, to diagnose cardiopathies from ECG images.

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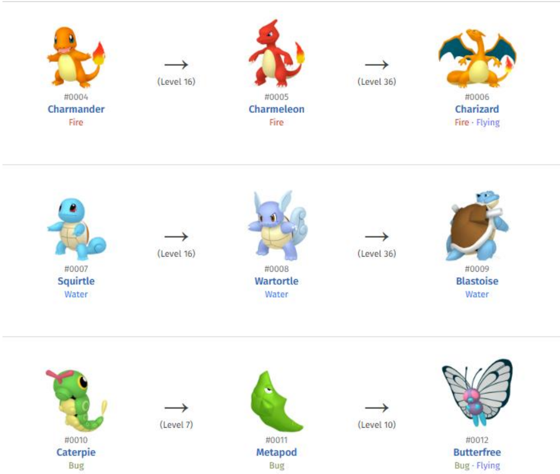
Appendix

<u>An Introduction to Pokémon</u>

A Pokémon is a fictional creature which is the basis for certain Japanese and Japan-inspired games and cartoons. It has stats, a type, a generation, and an evolution paradigm, as shown in the figure underneath:



A list of the categories under which a Pokémon can fall is as under:

<u>Existing Pokédexes compared to our Pokédex, the Pokémondium:</u>