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CLASSIFYING INVASIVE ALIEN SPECIES IN THE PHILIPPINES USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract

The proliferation of Invasive Alien Species (IAS) in the Philippines is a major threat to its biodiversity. Towards reducing such threat, deep learning technology can be applied to collect taxonomic information which may then assist in strategies and plans to fight IAS. This study presents implementations of Resnet18, MobileNetV2 and GoogLeNet, three known convolutional neural network (CNN) models, previously used for other deep learning tasks, for classifying twenty-four (24) IAS in the Philippines (PH). In this interdisciplinary study, a dataset of 2,581 images of 24 invasive species was first collected. The initial images were obtained from the ASEAN Centre for Biodiversity (ACB) and supplemented by images from the International Union for Conservation of Nature (IUCN) database, the Global Biodiversity Information Facility (GBIF) and Google Images. The images were pre-processed and then used to train the three CNN models to classify the 24 invasive species. We used five-fold cross validation to evaluate the performance of our models. Precision, recall, f1-score and overall accuracy metrics were recorded and showed that the three models can accurately classify the twenty-four IAS PH in our dataset. The top performing model, ResNet18, achieved a 90.8% average accuracy while MobileNetV2 and GoogLeNet achieved average accuracies of 87.4% and 87%, respectively. While ResNet18 had higher average accuracy than the other two models, a one-way analysis of variance test of the accuracies of the three models across the five-fold training and validation, however, showed no statistically significant difference.

Keywords: Alien species Philippines, Biodiversity, Convolutional neural networks, Deep learning, Invasive.

1. Introduction

Invasive Alien Species (IAS) are defined as “animals, plants, and other organisms whose introduction and/or spread outside of their natural past or present distribution threatens biological diversity” [1]. The proliferation of IAS poses a major threat to biodiversity. The introduction and spread of IAS outside of their natural habitats causes economic and environmental problems. IAS disrupts the ecological balance of the area being invaded. Invasive species can disrupt native species by introducing disease, preying on them and taking up their space, food and other resources. The native species lose their natural habitat and food, which can lead to their extinction [2-4].

One of the ways that may help reduce this threat is to develop taxonomic information on IAS and leverage technology in the fight against IAS. Towards this end, a deep learning model that automatically identifies invasive species from an input image can be quite helpful.

In this study, we implement three known high-performing Convolutional Neural Network (CNN) models – Resnet18, MobileNetV2 and GoogLeNet – to classify images of twenty-four (24) invasive alien species in the Philippines. We investigate how these three CNN models perform in classifying images of the 24 invasive alien species in the Philippines.

2. Related Work

ResNets were introduced in the paper “Deep Residual Learning for Image Recognition” by Kaiming He et al. from Microsoft Research [5]. ResNet18 is a CNN architecture that is 18 layers deep. Experiments showed that ResNets gain accuracy from increased depth [5]. ResNet18, the smallest of the ResNets, has 11.7 million parameters. ResNets were trained on the benchmark ImageNet-1k dataset.

MobileNetV2 was introduced in the paper “MobileNetV2: Inverted Residuals and Linear Bottlenecks” by Mark Sandler et al. from Google Inc. [6]. “MobileNetV2 is a convolutional neural network architecture that seeks to perform well on mobile devices” [6]. The model has 3.5 million parameters and was trained on the ImageNet dataset.

The GoogLeNet model is based on the “Going Deeper with Convolutions” paper [7]. GoogLeNets is a 22-layer deep CNN architecture whose main hallmark is the improved utilization of computing resources. The model has 6.6 million parameters. It was trained on the ImageNet dataset and was the winner of the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC 2014).

Among the studies we reviewed, 2 techniques have been applied to local or IAS related datasets. TensorFlow Inception v3, a CNN model implementation, was used to identify 41 Philippine frog species of the genus Platymantis [8]. The model was applied to audio spectrograms of frog calls. The study explored the performance of the “model in discriminating closely-related frog species and the potential of the platform to accelerate new species discovery”. The performance of the model was “compared to find an optimum balance between computing time and classification efficiency” [8].

The study entitled "Classifying mosquito presence and genera using median and interquartile values from 26-filter wingbeat acoustic properties" showed that a "simple model based on mean and interquartile values outperformed a CNN model in identifying the mosquito genus from 3 mosquito classes" [9] and in detecting mosquito presence. This study reminds that state of the art techniques may not necessarily be the most accurate or most efficient solutions every time. [9].

3. Methodology

3.1. Data collection and preparation

A dataset of 2581 images of twenty-four (24) invasive alien species in the Philippines (IAS PH) was first collected and then used in this interdisciplinary study. These IAS PH are listed by the International Union for Conservation of Nature (IUCN) as invasive to the Philippines. The initial images were obtained from the ASEAN Centre for Biodiversity (ACB) and supplemented by images from the IUCN database, the Global Biodiversity Information Facility (GBIF) and Google Images.

The twenty-four invasive species are enumerated in Table 1 together with their corresponding distribution and with a sample image for each species. We will refer to this dataset as IAS PH for brevity. This dataset of 24 IAS PH is not yet comprehensive as there are more than 100 species listed in the Global Register of Introduced and Invasive Species - Philippines [10]. This image dataset of IAS PH is a work in progress.

All the IAS PH images were carefully collected to represent their classes. Some of the images were pre-processed by cropping on the part of the image that showed the IAS. Some images came to us already pre-processed. For example, the images in Table 1 showing invasive frogs in a white background were already pre-processed by removing background 'noise' and focusing on the image of the invasive frog itself.

3.2. Model implementation

Three CNN models namely ResNet18, MobileNetv2 and GoogLeNet. were implemented and trained on the IAS PH dataset.

Pre-trained models were used to set the CNN layers of our models and their initial parameters. The number of epochs were set to 10 for all models for easy comparability and evaluation. The best model can be saved again at its best epoch when re-trained for deployment. The batch size was set to 32 and the learning rate was initially set to the standard at .001. Experiments showed that a batch size of 32 was the optimum choice for the hardware set-up utilized.

3.3. Model training and validation

A five-fold cross validation was implemented in this study to estimate the expected classification accuracy of each model. The IAS PH dataset was partitioned into five folds. A summary of this partitioning is provided in Table 2.

Table 1. IAS PH dataset.

Callosciurus finlaysonii - Finlayson's squirrel		120 instances	Kaloula pulchra (Asian painted frog)		77 instances
Eichhornia crassipes - Water hyacinth		62 instances	Lissachatina fulica - Giant African land snail		251 instances
Eleutherodactylus *planirostris (Greenhouse Frog)*		32 instances	Mus musculus - House mouse		130 instances
Gambusia affinis - Mosquitofish		163	Nipaecoccus nipae - Coconut mealy bug		75 instances
Hoplobatrachus rugulosus (Chinese edible frog)		39 instances	Oreochromis niloticus- Nile tilapia		141 instances
Hylarana erythraea (Green Paddy Frog)		52 instances	Parachromis managuensis - Jaguar guapote		103 instances
Paratrechina longicornis - Longhorn crazy ant		173 instances	Pterygoplichthys spp. - Janitor fish		87 instances
Pelodiscus sinensis- Chinese softshell turtle		160 instances	Rattus exulans - Pacific rat, Polynesian rat		100 instances
Pheidole megacephala - Big-headed ant		116 instances	Rattus tanezumi - Asian house rat		111 instances
Pheretima spp. - Giant earthworm		52 instances	Rhinella marina - Cane toad, Palakang tubo, kamprag, baki		52 instances
Phyllorhiza punctata - Bell jellyfish		138 instances	Scotinophara coarctata - Rice black bug		35 instances
Pomacea canaliculata- Golden apple snail, Golden kuhol		171 instances	Trachemys scripta elegans - Red-eared slider		141 instances

Table 2. IAS PH five-fold partitioning.

Class	IAS PH	fold1	fold 2	fold 3	fold 4	fold 5	total
1	Callosciurus finlaysonii - Finlayson's squirrel	24	24	24	24	24	120
2	Eichhornia crassipes - Water hyacinth	12	12	12	13	13	62
3	Eleutherodactylus planirostris - Greenhouse frog	7	6	7	6	6	32
4	Gambusia affinis - Mosquitofish	33	33	30	33	34	163
5	Hoplobatrachus rugulosus - Chinese edible frog, Palakang bukid	9	7	9	7	7	39
6	Hylarana erythraea - Green paddy frog	11	10	11	10	10	52
7	Kaloula pulchra - Asian painted frog, banded bullfrog	16	15	16	15	15	77
8	Lissachatina fulica - Giant African land snail	50	50	50	50	51	251
9	Mus musculus - House mouse	26	26	26	26	26	130
10	Nipaecoccus nipae - Coconut mealy bug	12	16	16	16	15	75
11	Oreochromis niloticus- Nile tilapia	26	26	29	30	30	141
12	Parachromis managuensis - Jaguar guapote	20	20	21	21	21	103
13	Paratrechina longicornis - Longhorn crazy ant	34	34	34	35	36	173
14	Pelodiscus sinensis- Chinese softshell turtle	31	32	33	33	31	160
15	Pheidole megacephala - Big-headed ant	23	23	23	23	24	116
16	Pheretima spp. - Giant earthworm	9	10	11	11	11	52
17	Phyllorhiza punctata - Bell jellyfish	25	28	29	27	29	138
18	Pomacea canaliculata- Golden apple snail, Golden kuhol	34	33	34	35	35	171
19	Pterygoplichthys spp. - Janitor fish	17	17	17	18	18	87
20	Rattus exulans - Pacific rat, Polynesian rat	20	20	20	20	20	100
21	Rattus tanezumi - Asian house rat	22	21	22	23	23	111
22	Rhinella marina - Cane toad, Palakang tubo, kamprag, baki	11	10	11	10	10	52
23	Scotinophara coarctata - Rice black bug	6	8	7	7	7	35
24	Trachemys scripta elegans - Red-eared slider	25	29	29	29	29	141
	total	503	510	521	522	525	2581

In each of the 5 iterations of the cross-fold (training and) validation, the training set comprising of the four folds outside the hold-over validation fold underwent data augmentation to vary and thus increase the number of training instances the model sees. Specifically, the original training images were first randomly cropped and resized to 256x256. They were then randomly rotated within 15 degrees, randomly horizontally flipped and centre-cropped to 224x224. The images were then transformed into tensors and normalized. The data augmentation was only performed on the training set, and not on the validation set. These random transforms produced different transformations across calls.

For each cross-fold validation iteration, the training and validation phases were set to 10 epochs. Furthermore, for each epoch the images were loaded into memory in batches of 32 images.

In the model training phase, for each loaded batch, cross entropy loss was calculated, and the parameters were updated using backward propagation and stochastic gradient descent. The learning rate (LR) was initially set to 0.001 and decreased by 0.1 every 7 epochs.

3.4. Statistical testing for significance

As each of the models were trained on the same IAS PH training set, we checked whether there is a statistically significant difference between the three models' performance. To do this, a one-way analysis of variance (ANOVA) test was performed between the model accuracies across the five-fold runs. The level of significance was set to the standard 0.05.

3.5. Deployment of a trained model online

The best performing model was chosen for deployment. A prototype web application to test the performance of the model was developed using an open-source library.

An online repository was created to contain the code and CNN model. The code and model were then uploaded to the online repository.

A cloud account was created to enable sharing of the prototype web application and public testing of the CNN model. A web application linked to the online repository was then deployed.

4. Results and Discussion

4.1. Training and Validation Metrics

In this study, the following metrics were taken for each model: model size, training time, accuracy, precision, recall, f1-score. Five-fold cross validation was used, and metric performances were recorded for each of the five-fold runs of the three models.

A summary of the average metrics for the five-folds runs of the three CNN models is shown in Table 3.

ResNet18 with an average accuracy of 90.8% is the best performing model on the IAS PH dataset. MobileNetv2 comes second with 87.4% accuracy. GoogLeNet ranks last on the IAS PH dataset with 87%.

MobileNetv2 is the smallest when it comes to model size at 9.2MB. Followed by GoogLeNet and ResNet18 with model sizes of 22.6MB and 44.8MB, respectively. Model size is a function of complexity. The more complex the model, the more layers and parameters it has then the bigger its size.

Table 3. Average training and validation metrics of the five-fold runs.

Average Metrics	ResNet18	MobileNet	GoogLeNet
Model Size (megabytes)	44.8MB	9.2MB	22.6MB
IAS PH (24 classes, 2581 images)			
Median Training time with GPU - 1 run	3m24s	3m23s	3m57s
Accuracy	0.908	0.874	0.870
Macro			
Precision	0.912	0.886	0.876
Recall	0.904	0.862	0.842
F1-score	0.904	0.868	0.846
Weighted			
Precision	0.914	0.882	0.882
Recall	0.908	0.874	0.870
F1-score	0.908	0.870	0.870

Precision is the percentage of positive predictions that were predicted correctly while recall is the percentage of the actual total instances in the class that were predicted correctly.

The f1-score combines precision and recall. It is the harmonic mean of the two scores and is used to rate the accuracy of the model on each class and the dataset in general

On IAS PH, the performance ranking for all metrics follow the same order as in the overall accuracy metric except for some metrics that yielded a tie between MobileNetv2 and GoogLeNet. ResNet18 again ranked first in terms of precision, recall and f1-score, followed by MobileNetv2 and then GoogLeNet.

4.2. Aggregated confusion matrix and classification report

Table 4 shows the mapping between class numbers and class names in IAS PH for reference. The aggregated confusion matrix (ACM) for ResNet18, the best performing model, is shown in Table 5. This ACM is representative of the ACMs of all models. A common result reflected in the ACMs of the three models is the confusion of similar species with one another.

For example, the ACM for ResNet18 shows that the mouse/rat classes are being confused for one another. Fourteen (14) instances of class 9 (house mouse) are incorrectly identified as class 20 (Rattus exulans) and six instances are mistaken as class 21 (Rattus Tanezumi). Furthermore, it also shows that classes 20 (Rattus exulans) and 21 (Rattus tanezumi) are being confused for each other with 16 false negatives each.

The ants, classes 13 (long-horn crazy ant) and 15 (big-headed ant), come in second as most confused with each other, with six (6) and seventeen (17) false negatives of each other, respectively.

Table 4. Class numbers to class names mapping.

Class	IAS PH
1	Callosciurus finlaysonii - Finlayson's squirrel
2	Eichhornia crassipes - Water hyacinth
3	Eleutherodactylus planirostris - Greenhouse frog
4	Gambusia affinis - Mosquitofish
5	Hoplobatrachus rugulosus - Chinese edible frog, Palakang bukid
6	Hylarana erythraea - Green paddy frog
7	Kaloula pulchra - Asian painted frog, banded bullfrog
8	Lissachatina fulica - Giant African land snail
9	Mus musculus - House mouse
10	Nipaecoccus nipae - Coconut mealy bug
11	Oreochromis niloticus- Nile tilapia
12	Parachromis managuensis - Jaguar guapote
13	Paratrechina longicornis - Longhorn crazy ant
14	Pelodiscus sinensis- Chinese softshell turtle
15	Pheidole megacephala - Big-headed ant
16	Pheretima spp. - Giant earthworm
17	Phyllorhiza punctata - Bell jellyfish
18	Pomacea canaliculata- Golden apple snail, Golden kuhol
19	Pterygoplichthys spp. - Janitor fish
20	Rattus exulans - Pacific rat, Polynesian rat
21	Rattus tanezumi - Asian house rat
22	Rhinella marina - Cane toad, Palakang tubo, kamprag, baki
23	Scotinophara coarctata - Rice black bug
24	Trachemys scripta elegans - Red-eared slider

The aggregated classification report for ResNet18 is shown in Table 6. TP, FN and FP are the per class true positives, false negatives and false positives, respectively. This report, which is representative of the classification reports of the three CNN models, further shows that confusion between similar classes are pulling overall performance metrics down.

Classes that are very similar such as classes 9, 20 and 21 (the rat/mouse classes) and the ant classes (13 and 15) registered the highest number of false positives and negatives in the classification report. These affected precision, recall and f1-score metrics, as well as overall accuracy metrics as these metrics are computed using these basic values.

Some classes that are similar (e.g. the frog classes), although still being confused for another similar species have less instances of confusion compared to the mouse/rat and ant classes with just one or two false negatives or false positives,

To what do we attribute the differences in confusion in the classification between similar classes? Visual inspection and analysis of our ACMs and the images in our datasets provide us with these insights: (1) image quality, (2) image quantity, (3) image variety and (4) clear image differentiation are primary factors in the classification performance of our models, in general, and in its performance in classifying similar classes, in particular.

With these insights in mind, image enhancement and augmentation techniques can be explored to increase the performance of our models.

Table 5. Aggregated Confusion Matrix - ResNet18

Class	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	112	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1	4	0	0	0
2	0	61	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
3	0	0	30	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	149	0	2	0	0	0	3	1	1	4	0	1	1	0	0	1	0	0	0	0	0
5	0	0	1	0	35	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0
6	0	0	0	0	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	76	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
8	0	0	0	0	0	0	0	236	0	0	0	0	1	3	0	1	3	7	0	0	0	0	0	0
9	2	0	0	0	0	0	0	0	102	1	0	0	1	0	1	0	1	2	0	14	6	0	0	0
10	0	2	0	0	0	0	1	0	0	69	0	0	3	0	0	0	0	0	0	0	0	0	0	0
11	1	0	0	2	0	0	0	2	1	2	129	0	0	2	0	0	1	0	1	0	0	0	0	0
12	0	0	0	4	0	0	0	0	0	1	0	94	0	0	0	0	1	0	3	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	1	0	0	166	0	6	0	0	0	0	0	0	0	0	0
14	0	0	0	0	1	0	1	1	0	0	0	0	2	152	0	0	0	1	0	0	0	0	0	2
15	0	0	0	0	0	0	0	0	0	1	0	0	17	0	98	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	50	0	1	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	135	2	1	0	0	0	0	0
18	0	0	0	0	0	0	0	4	0	1	0	0	2	0	0	0	0	164	0	0	0	0	0	0
19	1	0	0	0	0	0	0	0	0	0	0	1	0	4	0	0	0	1	77	0	1	2	0	0
20	0	0	0	0	0	0	0	0	11	0	0	0	1	0	0	0	0	1	0	70	16	0	1	0
21	1	0	0	0	0	0	0	0	10	1	0	0	1	1	0	0	1	0	0	16	80	0	0	0
22	0	0	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	45	0	0
23	0	0	0	0	0	0	0	1	0	0	0	0	4	0	1	0	0	2	0	0	0	0	27	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	1	137

4.3. Statistical comparison of the models

The accuracy metric, a standard performance metric used in image classification tasks, represents overall CNN performance. Although other metrics were recorded for each of the models, only the accuracy metric was used to compare the performance of the three implemented models. The actual accuracy metrics of the three models for each run across the five-fold training and validation are shown in Table 7.

Table 6. Aggregated Classification Report - ResNet18.

Class	Instances	TP	FN	FP	Precision	Recall	F1-score	Class
1	120	112	8	5	0.957	0.933	0.945	1
2	62	61	1	3	0.953	0.984	0.968	2
3	32	30	2	5	0.857	0.938	0.896	3
4	163	149	14	6	0.961	0.914	0.937	4
5	39	35	4	3	0.921	0.897	0.909	5
6	52	52	0	2	0.963	1.000	0.981	6
7	77	76	1	3	0.962	0.987	0.974	7
8	251	236	15	8	0.967	0.940	0.954	8
9	130	102	28	22	0.823	0.785	0.803	9
10	75	69	6	15	0.821	0.920	0.868	10
11	141	129	12	1	0.992	0.915	0.952	11
12	103	94	9	2	0.979	0.913	0.945	12
13	173	166	7	36	0.822	0.960	0.885	13
14	160	152	8	12	0.927	0.950	0.938	14
15	116	98	18	10	0.907	0.845	0.875	15
16	52	50	2	2	0.962	0.962	0.962	16
17	138	135	3	7	0.951	0.978	0.964	17
18	171	164	7	19	0.896	0.959	0.927	18
19	87	77	10	7	0.917	0.885	0.901	19
20	100	70	30	31	0.693	0.700	0.697	20
21	111	80	31	27	0.748	0.721	0.734	21
22	52	45	7	4	0.918	0.865	0.891	22
23	35	27	8	3	0.900	0.771	0.831	23
24	141	137	4	2	0.986	0.972	0.979	24
Total	2581	2346		Average	0.908	0.904	0.905	

Table 7. Model accuracy for each of the five-fold runs.

	run 1	run 2	run 3	run 4	run 5
ResNet accuracy	0.910	0.910	0.930	0.950	0.840
MobileNetv2 accuracy	0.880	0.870	0.880	0.920	0.820
GoogLeNet accuracy	0.860	0.870	0.910	0.930	0.780

As mentioned, a one-way analysis of variance (ANOVA) test was performed between the model accuracies shown in Table 7.

The results of the one-way ANOVA test are shown in Table 8.

The ANOVA test reveals that there is no statistically significant difference in the performance of the three models on the IAS PH dataset. The p-value of 0.386 is not less than the 0.05 standard significance level.

In summary, the results indicated that ResNet18, MobileNetv2 and GoogLeNet can accurately classify the 24 IAS PH in the dataset.

Table 8. One-way ANOVA test between accuracy metrics of the three CNN models.

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
ResNet	5	4.54	0.908	0.00172		
MobileNetv2	5	4.37	0.874	0.00128		
GoogLeNet	5	4.35	0.87	0.00335		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.00436	2	0.00218	1.02992	0.38655	3.88529
Within Groups	0.0254	12	0.00212			
Total	0.02976	14				

4.4. Online deployment of model

A prototype web application for testing the IAS PH CNN model may be accessed online. The web application, at present, is a proof of concept that the models developed are deployable and have a practical application. They can also be useful in scientific research.

Future versions of the application will allow collection of crowd-sourced images. Everyone can use the application to upload their own images of IAS. In this way, the dataset can be grown, and the models made more accurate. Improved versions of the application may also help detect, control, mitigate and prevent the introduction and spread of IAS.

5. Conclusions

In this study, we developed and introduced IAS PH, a dataset of 24 invasive alien species in the Philippines. We implemented and trained three CNN models, namely ResNet18, MobileNetv2 and GoogLeNet, on the IAS PH dataset to show how to classify IAS PH accurately. We recorded performance metrics and evaluated the performance of the models on those metrics. We found that ResNet18 performed best on IAS PH among the three models implemented. We also found, however, using the ANOVA test that there was no statistically significant difference between the accuracies of the three models.

We recommend growing the dataset to increase the training set size with real-world examples. We also recommend exploring image enhancement and augmentation techniques to improve the performance of our CNN models. We lastly recommend enhancement of the prototype web application and further deployment of the deep learning CNN models on other web and mobile platforms primarily to make these publicly available to users. This may help detect, prevent or control the introduction and/or spread of IAS which can cause economic, environmental and health problems.

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