Automated Methods to Identify Snake Species in Sri Lanka: A Review

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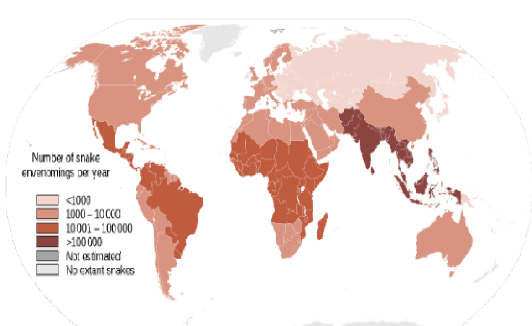
***Abstract*— *Snake bites in Sri Lanka cause death to nearly 100 people each year. Among the many reasons for this condition is the inability of people to identify the snake type which prevents administering the appropriate anti-venom treatment. Misidentification of snakes also causes threats to the existence of harmless snakes that contributes to the biodiversity of reptile species. A survey conducted with 223 participants to ascertain the ability of people to correctly identify the snake type when an image of a snake is available revealed that the majority out of the participants was unable to recognize the snake type. This paper presents some of the survey results and a review of various methods such as k-nearest neighbors (KNN), Support Vector Machines (SVM), Image Processing techniques, Probabilistic Graphical Models, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN) which are used to automatically identify objects, birds, marine species, humans and animals that could be applied for snake recognition to assist people in identifying snake types which can contribute in reducing morbidity and mortality due to snake bites as well as to minimize the harm caused to innocent snake types.*

***Keywords*— convolutional neural networks, snakes, automatic snake identification**

I. INTRODUCTION

Sri Lanka is home to about 105 species of snakes (Maduwage, n.d.) with about half of them being endemic to Sri Lanka. The reason for this abundance is due to the diversity in the climatic conditions despite Sri Lanka being a small island. Statistics show that the highest number of envenoming and fatalities due to snakebites occur in the region of South Asia to which Sri Lanka belongs (Ralph et



distribution

al., 2019). Figure 1 shows the world-wide distribution of envenoming due to snake bites illustrating the region with the highest death rates marked dark brown.

According to the Sri Lanka Medical Association (SLMA), about 200 snake bites and 100 fatalities caused by snakes are reported in Sri Lanka annually. Other estimates that include unreported cases of snake bites and resulting deaths reveal that nearly 400 people are bitten by snakes annually and about 100 out of them die (Rodrigo, 2018). Snakebite statistics in Sri Lanka between the years 2004 to 2014 are shown in Table 1.

Table 1. Cases of envenoming and deaths due to snakebites in Sri Lanka from 2004 - 2014

Year	Cases	Deaths
2009	39,728	86
2010	42,146	88
2011	-	-
2012	41,462	76
2013	40,373	95
2014	37,215	94

Source: Medical Statistics

Sri Lanka Medical Association (SLMA) states that snakes are classified as highly venomous, venomous and mildly venomous snakes (Fernando, 2017). Out of the large number of snake species found in Sri Lanka, only about 6 types are highly venomous, and the vast majority of them are harmless. The highly venomous types are Cobra, Ceylon Krait, Common Krait, Russel's Viper, Saw Scaled Viper and Hump-nosed Viper that cause a significant number of snakebites to humans as well fatalities.

According to SLMA reports on snakebites, the identification of the snake that was involved in the snakebite is of utmost importance to administer proper treatment (Fernando, 2017). Furthermore, ignorance about snake types causes

people to unnecessarily kill harmless snakes threatening the bio-diversity that enrich nature.

In order to assess the ability of Sri Lankans to identify snakes in the island a survey was conducted, and some results of the survey are described with a statistical analysis which revealed that many who participated in the survey were unable to identify most of the snake images used. Some of the major findings of the survey, which included people from different age groups, different provinces as well as both females and males are also presented.

Many researchers have employed different methods including neural networks to identify wild animals, birds, fruits, objects, humans etc. Such existing and proposed systems and applications are reviewed in this paper with the intention of selecting and applying a suitable method for snake identification.

In Section II of this paper, a literature review on animal identification systems using CNN as well as other methods are presented. This is followed by a description of the methodology used in the study in Section III. An analysis of the survey results is presented in Section IV and Section V gives a discussion of the results. The proposed solution for reducing morbidity and mortality due to snake bites is stated in Section VI. The conclusion of the study is given in Section VII.

II. LITERATURE SURVEY

Classification of snakes, wild animals, farm animals, birds, marine species, fruits, vehicles, images of sceneries, objects as well as age and gender of humans have been conducted using various methods such as image processing techniques, Radiofrequency Identification (RFID) technology, Support Vector Machines (SVM), Neural Networks (NN), k-nearest neighbour algorithm (KNN) as well as the proposed method in this research work, Convolutional Neural Networks (CNN). All these classification methods have been implemented to reduce the cost incurred and the time consumed when it is done manually.

A study directly addressing the problem domain of this research work has been conducted and presented in the research conducted by A.P. James et al, (James et al., 2014) where thirteen probabilistic graphical models and 12 attribute enhancing methods have been used to identify the most relevant features in snakes for classification purposes. These features have been grouped depending on the view of the body; namely upper, lower, left and right parts of snakes. The samples have contained images of 6 types of snakes found in India. Out of the initially chosen 38 features, the results have shown that a total of 15 taxonomy features are sufficient to classify the type of the snake. The study has achieved the highest accuracy rate of 87.5% for IBk classifier (Aha et al., 1991) in identifying the necessary 15 features of the snake.

Identification and monitoring of cattle has been conducted using RFID technology (Eradus and Jansen, 1999). The RFID tags which have been placed on the cattle have not only been useful in detecting the animal but also in monitoring its health. Stating an accuracy rate of 75%, this study has hinted the use of NN for future farm animal detection systems. A text message alert system integrated with RFID for identifying farm animals has been proposed by V.M. Anu and others in their Literature Review regarding RFID for farm animal identification (Anu et al., 2015). As a solution for identifying many objects concurrently, a much more enhanced RFID method has been employed by H Vogt where around 30 tags were concurrently identified with an accuracy of 96% (Vogt, 2002).

Vegetable and fruit classification have also been an area of interest in computer vision. Hence, many studies have been carried out to identify and classify various aspects of fruits and vegetables. To identify the standard quality of tomatoes, a method using 5 image processing algorithms for correct texture, texture homogeneity, shape, stem and injury free identification, which has included operations such as morphology, has resulted in an accuracy of over 90% for correct texture, 80% in identifying defect free tomatoes (Laykin et al., 2002). The color of the tomatoes was identified using Mean Standard Deviation method, Slide Block method and Quad Tree method (Laykin et al., 2002). Employing Sobel edge detection and evaluating the histograms obtained, the homogeneity of color for each tomato was detected. Similarly, the shape was also detected. A rule-based identification system has been implemented for all categories. All the image processing portions of the study has been implemented using Matlab. Image processing techniques have also been employed in size identification of fruits and vegetables such as tomatoes and lemons (Lino et al., 2008). In that particular study, a software (ImageJ) which offers capabilities in calculations of means and detection of edges has been used.

Another area that has been explored in computer vision is the identification of birds. SVM based bird image identification system has resulted in an accuracy of over 98% in testing (Roslan et al., 2017). Bringing out a solution to the fact that images of birds are of various sizes as well as angles, this study has classified images of two kinds of bird species. Prior to classifying, image processing techniques such as Edge detection using Sobel Operator and morphology have been applied as pre-processing steps. A similar system which has also used six image processing techniques as well as SVM to identify three types of animals, namely tiger, dog and cat has achieved respective highest accuracies of 94%, 93% and 93% for the edge histogram descriptors pre-processing technique (Shalika and Seneviratne, 2016).

Classification of animals can be considered as the wide area of this proposed research work. This has been carried out using various machine learning methods including KNN, SVM, ANN and CNN. An animal classification comparison has been carried out by a system using KNN and probabilistic NN (PNN) where the analysis of the image for segmenting has been done using a graph-cut method (Kumar et al., 2015). For 25 chosen categories of animals with 64 block images, an accuracy of about 52% has been recorded for 70% portion of training when using PNN. In contrast, the KNN has shown an accuracy of about 60% for the same type of block images pointing out their recommendation of KNN.

ANN approaches in classification and identification has been widely adopted by many researchers. ANN based systems showcase efficiency as pre-processing of images are done separately from the model. Such a system, which has used ANN for the identification of gender with the use of features recognized in the face, while the extraction of features has been carried out using Viola-Jones algorithm (Viola and Jones, 2001) has been proposed by A Jaswante and others where an accuracy of about 98% has been recorded (Jaswante et al., 2013). The efficiency of the proposed system has been pointed out by the researchers in this study stating that it will be of great use for a real time system because of its efficiency. Moving a step further, a gender identification system which also identifies age has been discussed in the work carried out by T Kalansuriya and others with the use of images of faces of people (Kalansuriya and Dharmaratne, 2014). This system has used image processing techniques for pre-processing and feature extraction stages while the classification has been done using ANN. Four age classes have been categorized to train and test the system for faces of both Asian and non-Asian continents. The human ability to identify the age and gender of a person has been quantitively compared with the system's ability for the same. Although humans can identify the gender with a 100% accuracy, the age identification is of an accuracy rate of about 67% while the proposed system has achieved accuracies of about 85% and 74% respectively for the same. Another ANN based gender classification system which has used kinematic data of eight walking movement features to identify the gender of children has used algorithmically produced data as well as originally obtained data (Zakaria et al., 2015). A comparison of the two datasets that have been trained using ANN has shown an accuracy increase of up to 86% when algorithmically produced data was also included.

Another type of NN known as CNN is rapidly gaining recognition in machine learning and classification problems. The proposed solution for the problem identified in this research work is also based on CNNs and therefore CNN based identification systems have been of primary focus in this literature review. The prominent work of the classification of ImageNet using a 5 layered CNN has included good quality images of 1000 categories where error rates of about 37% and 17% have been stated for the topmost identification and top 5 most identification (Krizhevsky et al., 2017). With the use of many GPUs and max pooling layers in the CNN, this work is considered to be ground-breaking. Another general classification of images using CNN which has included the identification of images with faces against images without faces, images of buildings, images of sites of agriculture, images of highly populated urban areas and images of forests as well as images with scenes such as beaches, gardens, streets, roads and battle sites against each other (Jaswal et al., 2014). The best results were obtained for the identification

of images with faces against images without faces which has been recorded as about 92% accurate on testing data while the lowest has been recorded as about 51% again on testing data.

The previously discussed topic of age and gender classification has been tackled using CNN as well by G Levi and other, where the proposed system has surpassed the previous work that had been done at that time regarding gender and age classification by recording accuracies of 86.8% for gender identification and 50.7% for exact age identification and 84.7% for one category off age identification (Levi and Hassncer, 2015).

CNN based systems have also been proposed in identifying marine animals. One such study has been carried out to identify two types of fish where CNN is integrated with a set of hand-designed images (Cao et al., 2015). With the use of DeCaf framework, the researchers have stated the overall error rate to be of about 1.38% when only CNN was used while 1.08% is the recorded error rate when both images are used together. In contrast to recognizing a specific species type, a method for recognizing a specific individual animal has been proposed in a Minke Whale recognition study (Konovalov et al., 2018). Using the stable unique color pattern of each Minke Whale, a model has been developed to identify each individual whale using CNNs. An accuracy of 93% has been achieved which has been stated as a higher rate than that of a Gorilla recognition study.

The use of CNN has been very popular among studies based on wildlife monitoring. Employing the well-known method of camera traps which are based on motions for collecting images, these studies have shown promising results further confirming CNN as an accurate approach for classification. One such study has stated comparative accuracies of three different CNN architectures employed in their work (Nguyen et al., 2017). In the study, the highest accuracy rate of 96.60% for animal detection has been observed for VGG-16 CNN architecture while those for the recognition of the three most frequently found animals and the six most frequently found animals were shown to be 90.40% and 83.93% respectively for ResNet-50 CNN architecture. A CNN based wild animal identification system has shown a quantitative comparison between the system that the work has proposed and the Bag-of-Words (B0W) model where segmentation has been carried out using graph-cuts (Chen et al., 2014). Though the accuracy of the said proposed system is higher than that of the BoW method, the accuracy rate has been recorded as about 38% which is comparatively very low value for a CNN based system. As the reasons for obtaining such low accuracies, the insufficiency in proper data and the small number of layers in the CNN can be pointed out. Yet another study which is very much similar to the former study discussed under animal classification using CNN, in which 48 types of species have been selected for identification, counting and for elaborating on their characteristics (Norouzzadeh et al., 2018). Out of the nine architectures that have been used to select the best achieving architecture, ResNet-152 has been identified. A whopping 95% accuracy rate has been recorded for the identification being in the top-5 while a 63% accuracy rate has been obtained for counting the animals.

III. SNAKE IDENTIFICATION SURVEY

As mentioned in Section II, a questionnaire containing 19 questions was distributed among people of different age groups and genders. 233 responses were received, and the data collected was analysed.

For evaluating the responses, one point was given to each correct answer on snake image recognition questions. the total point distribution is shown in Figure 3. The average points scored by the participants was calculated as 6.93 out of a total of 14. The final question and the analysis obtained for it are shown in Figure 4.

More than 50% of the responses to the final question were strongly in favour of a mobile app to identify snakes. Altogether about 69% were in favour of the app while about 16% were neutral. Out of the group of 233 participants, only 13% had any additional knowledge on snakes. The highest accuracy rate was recorded for identifying the cobra which was 97%. This could be because the image that was provided clearly showed Cobra's iconic hood. The lowest accuracy rate of 15.6% was recorded for one of the two cat snake images. Out of the 233 participants, 3 have scored a perfect score of 14 out of 14. Even the 3 of them were in favour of a mobile app.

While the average points score by the participants was 6.93 out of 14, the average points score for the participants with additional knowledge in snakes was 8.30 which was somewhat higher than the general average score. However, it can be stated that even people with sound knowledge in snakes can misidentify the type on some occasions since this average is not significantly high.

As mentioned in Section III, for cat snake and rat snake, two images for each type were included. The identification accuracies for each image of the same type differed. Hence it can be said that most of the participants' knowledge regarding snakes is not solid enough.

Table 2. Identification accuracies of each snake type.

Snake Type	Identification Accuracy by the participants (%)
Cobra	97
Merrem's Hump-nosed Pit Viper	22.3
Saw Scaled Viper	59.7
Rat Snake (type 1)	75.1
Python	67.4
Common Indian Krait	61.8
Ceylon Krait	48.1
Cat Snake (type 1)	29.6
Indian Russell's Viper	52.8
Lowlands Hump-nosed Pit Viper	27.5
Blossom Krait	39.9
Rat Snake (type 2)	25.3
Cat Snake (type 2)	15.9
Sri Lankan Coral Snake	70.4
Cobra	97

Source: A Survey on the Ability to Identify Snake Types

As shown in Table 4, one image of the rat snake has been correctly identified by 75.1% of the participants while the

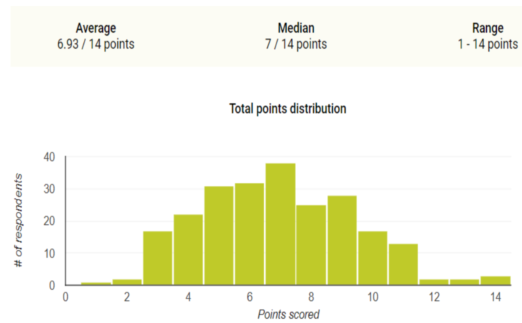


Figure 2. Total Points Distribution of the Survey. Source: A Survey on the Ability to Identify Snake Types - Google

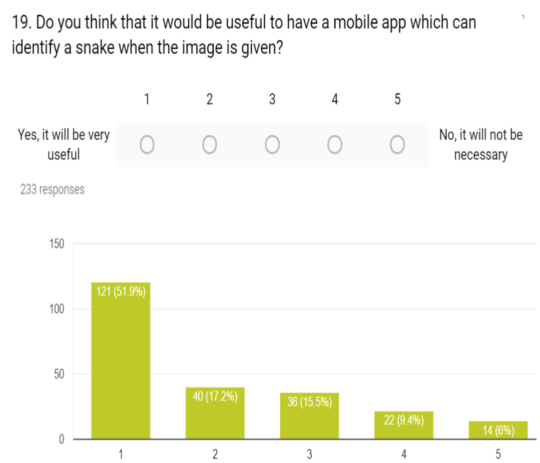


Figure 3. Final question of survey and responses. Source: A Survey on the Ability to Identify Snake Types

second image was correctly identified by only 25.3% with the majority identifying it as a common krait.

Data analysis of the collected results revealed that common types of snakes were easily identified while the comparatively rarer types were not identified properly by the majority.

IV. DISCUSSION

From the information collected regarding the fatalities due to snakebites, it was evident that the envenoming and fatality rates due to snakebites in Sri Lanka is high and that one reason for this high death rate is the inability of people to correctly identify the snake type. This was proven by the survey conducted in this study to find out about the ability of people to identify snake types. The survey revealed that out of 14 images of snakes found in

Sri Lanka, the survey participants were able to identify only about 7 snakes on the average. Since the questionnaire was distributed mostly among university students, there can be a high chance of a lower success rate if the general public's involvement was higher. When analysing all the papers used in the literature review collectively, a few conclusions can be drawn.

All the papers reviewed are based on classification problems and 16 papers out of the 20 papers reviewed were either animal, human, marine species or bird classifications and only one paper was based on snake classification and even that was done using probabilistic graphical models. 17 of these research studies were classifications using images. Out of the 8-research work carried out using CNN, only 2 have accuracies below 80% which can be considered as successful. Only 2 research studies out of the 20 reviewed had been carried out in Sri Lanka and those two are not done for snake classification.

This review reveals that out of all automatic identification methods, CNN based methods yield the most accurate results. Although ANN methods can also identify snake types, the accuracies are relatively less than that achieved through CNN methods and the pre-processing of the images is done inside the CNN classifier itself unlike in ANN. The only paper which discusses the classification of snakes describes the identification of the snake features that are most relevant rather than to classify them. The use of RFID is not practical when it comes to identifying the snake type since placing the RFID tag on a snake is impossible. The easiest way to identify snakes which differ from species to species by subtle features is by visual perception. When this is not possible, identification has to be made through an image. Classification of images using CNN gives higher accuracies compared to other machine learning approaches since CNN learns to identify fine features through the training process.

Furthermore, since mobile phones are common among the Sri Lankan public and mobile apps are regarded as a trend, snake identification using a mobile app would be beneficial to most people including hikers visiting forests.

V. PROPOSED SOLUTION

With the results of the survey, it was evident that the identification of snakes is not sufficiently accurate which can lead to unnecessary deaths of envenomed victims as well as of innocent snakes. Therefore, it is clear that as a solution to reduce any undue human deaths and snake killings an application for identifying the snake type using an image is of importance. For such an application to be used by hikers and villagers in areas with a large snake population, the app should be a mobile app. With the reviewing of the existing methods for identification, CNN was identified as the most suitable and innovative method to be employed for the creation of the mobile app. Hence, a mobile application using CNN to identify the type of snake when an image is given is proposed in this study as a solution. The mobile application is expected to be developed using either the Android Studio or Ionic Framework. The model to identify the snake of a given image will be trained using CNN.

Computer vision with deep learning has made significant advances with Convolutional Neural Networks (CNN). A CNN is an algorithm based on Deep Learning which can assign weights to different features/parts of an input image using suitable filters with very little pre-processing compared to other classification algorithms. CNN architecture resembles the connectivity pattern of neurons in the human brain and has been inspired by the layout of the visual cortex. CNN uses filters to segment images for easy processing without losing important features. By convolving the input image with a filter, a convolution layer is obtained for extracting low-level features such as sharp edges and color. This layer with extracted features is reduced in size by a pooling (max pooling or average pooling) layer to reduce the computational power required for data processing. These two layers comprise one layer of the CNN. Based on the complexity of the image, a desired number of such layers can be incorporated into the network to train the model to further extract low-level features. This is followed by flattening the output in order to feed it to a regular NN to classify images. Next, a fully connected layer is added to the system to learn high-level features through nonlinear combinations of high-level features computed by the convolution layer. This image is then flattened into a column vector and given as input to a feed-forward neural network. Backpropagation is then applied to every iteration of the training process. The model acquires the ability to discern dominant and low-level features of images to classify the images through a succession of epochs. The Softmax technique is employed to classify the images. Various CNN architectures have been developed. VGGNet, ResNet, MobileNet are some of them (Saha, 2018).

VI. CONCLUSION

Evidence for the high death rate due to snakebites were pointed out in the introduction while a review on a selected set of CNN based systems were discussed in the literature review. To highlight the importance of the identification of snakes to a greater extent, the results obtained from a survey were analysed to conclude that the accuracy in identifying snakes is not sufficient. Hence, with the integration of all the knowledge gathered through this study a solution of automatically identify snakes using CNN was proposed in Section V.

ACKNOWLEDGEMENT

The authors would like to sincerely thank all who rendered their support in this study.

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