Journal of Theoretical and Applied Information Technology
31st August 2021. Vol.99. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

USE OF DEEP LEARNING NEURAL NETWORKS FOR THE CLASSIFICATION OF BIRD SPECIES BASED ON THEIR SONG

[1]HOLMAN MONTIEL A., [2]FREDY MARTÍNEZ, [3]MIGUEL R. PÉREZ P.
Facultad Tecnológica, Universidad Distrital Francisco José de Caldas, Bogotá D.C, Colombia
E-mail: [1]hmontiela@udistrital.edu.co, [2]fhmartinezs@udistrital.edu.co, [3]mrperezp@udistrital.edu.co

ABSTRACT

An innate quality of living beings is the expression of their emotions in sound form. Birds stand out within living beings that perform sound communication, because they modulate their song to indicate moods or emotions as a protection or survival mechanism. This mechanism and the sound produced changes according to the taxonomic distribution of birds, since each species has its own physiognomy and even within the same species there can be different types of singing. Therefore, the study of the characteristic tonalities of each bird species and its song has become a topic of general interest in certain areas of biology, to determine the possible geographical locations or survival habits of each species. However, the classification of the tones generated in the song of a bird is a subject under study, due to the large number of sounds generated by a single species of bird. Therefore, this article proposes a strategy of classification and identification of the species of a bird by extracting characteristics of the tone of its song with a computational learning algorithm. Our scheme proposes the use of digitized bird sounds, which are processed by digital filters to extract the acoustic characteristics of interest. This filtering is performed in a two-stage scheme, which allows us to narrow down the region of interest of each digital file, which in the end constitutes the dataset of the learning system. To learn the typical characteristics of the sounds, different deep neural network structures are evaluated to identify the topology capable of replicating the characteristics of the samples. The results show a high performance of the identifier, which is linked to the characteristics of the network architecture.

Keywords: *Deep learning neural networks; Computer learning; Taxonomy; Classification; Signal processing*

1. INTRODUCTION

The hierarchical classification of living beings changes according to the physiological, morphological, or communicative characteristics of the established social groups. This has been widely studied and documented to establish a taxonomic map that classifies living beings into species depending on their geographical location. Bearing in mind that the species is the last of the taxonomic levels, since above it there are six other levels which group the individuals of each species by genus, family, order, class, phylum, and kingdom [1].

The taxonomic division has shown the biodiversity that exists at a regional level in many countries, among them Colombia has been highlighted as one of the most biodiverse countries in Latin America, because it has a figure of 742 species of birds discovered (a figure that increases every year). It is important to note that birds maintain a balance within an ecosystem by controlling pests, propagating seeds and pollination of crops [2-3]. For this reason, attempts have been made to study birds and their communication mechanisms, such as chemical, sound, or visual signals, used to find a mate, survive, or establish dominance. Among them, sound signals have represented a challenge for researchers, because species of the same family generate songs with different tonalities [4].

Normally, the songs are recorded with automatic long-term recording equipment that is protected to withstand the ambient conditions. This equipment is incorporated into the ecosystems in a non-invasive way, to capture the sounds of the songs in their natural state and reduce the effect of human intervention on the birds' habitats. For example, in Colombia, the Alexander Von Humboldt Institute for Biological Resources Research carried out automated acoustic monitoring (500 hours of recording) to evaluate the characteristics of a degraded and undegraded ecosystem from the songs of the bird species that make it up [4-5].

As can be seen, the above case shows that the volume of information generated during the study of bird song is overwhelming, since, as the duration of the monitoring or experiment increases, so does the amount of data collect [6]. Therefore, sound processing or pattern recognition techniques have been developed to identify characteristics of interest within the information collected from the ecosystem automatically, among which are classification and detection that are responsible for segmenting an audio signal to remove background noise and extract the biologically relevant characteristics. However, these techniques are computationally costly, which limits the number of characteristics that can be extracted from a sound, since trying to process a large volume of information in a short time requires a computer with great performance or the reduction of the amount of data to be processed [7-9].

This article proposes a partial solution to this limitation with a computational learning algorithm, which filters the input information to extract the relevant characteristics of a sound file. Once these characteristics are obtained, they are compared with a database of bird song records to determine the bird species. This contribution is presented in the following numerals, which are organized in the following way: in section 2 a description of the bird song is made, and some details of the classification technique used, in section 3 the technique developed is presented and in section 4 the results obtained with this technique are presented.

2. MATERIALS AND METHODS

The study of engineering tools for bio-acoustic signal processing has allowed us to explore certain characteristics of birds and their ecosystem remotely. This topic is addressed in this section from the biological mechanism used by birds to produce a sound, to the techniques that recover information from the tones detected in the song.

2.1. Bird song

Globally, bird ecosystems have not been fully studied and some are disappearing without knowledge of their existence. However, there are some exploration techniques that allow the structure of bird communities to be analyzed in a non-invasive way, by fixing a camouflaged recording device to the landscape to store the sounds that are produced within a certain radius for a period (around 500 continuous hours) [2-3].

Normally, recording devices capture all sounds in the environment, so the information collected must be filtered to extract the regions of interest and generate a new audio file. In addition, these devices are incorporated into the ecosystem through techniques that allow the monitoring of birds with an acoustic record, among which are point counting and transects. On the one hand, the point count refers to the auditory record of birds taken when making a sighting in each radius or area. On the other hand, in a transect the auditory samples are taken in an established perimeter in which the equipment is fixed and records continuously [4-5, 10].

The study of auditory records has established differences between the types of sounds that birds emit, which are called songs and calls. In the first case, songs are prolonged sounds and are related to courtship or mating. In the second case, the calls are made to announce predators or danger, to keep the group together during migration, to announce food locations or territorial limits. However, the songs and calls are produced by an organ located in the trachea called the syrinx, which is not fully developed in all species, so not all birds generate melodious tones [11].

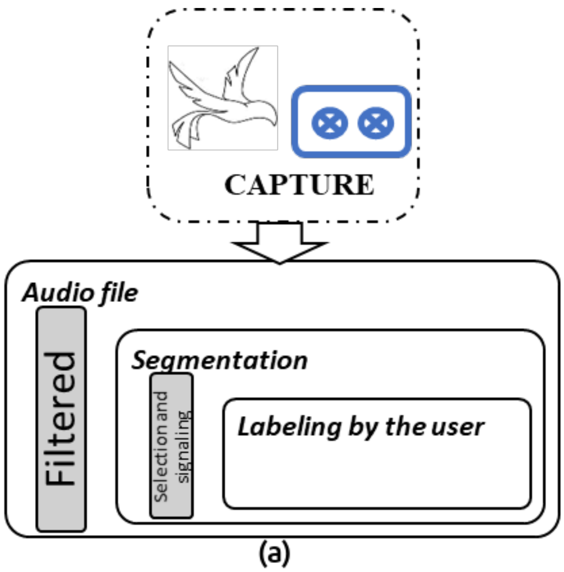
As can be seen, there are various techniques for capturing sounds from the environment, which are classified according to their biological function [12-14]. Therefore, mechanisms have been designed to identify the sound patterns in an audio file manually and automatically. First, the manual mechanism consists of having a person with knowledge of bird sound recognition listen to the entire content of the recording and characterize the tones found. Secondly, the automatic form is based on computer algorithms that detect, highlight, or separate the sections of interest in the audio files to classify or attempt to identify the bird. In both cases, pre-processing or filtering is required to remove the noise from the environment and extract as many features as possible, which will be discussed in detail in the next section.

2.2. Extraction or identification of characteristics in an auditory record

The sound records that store bird song are audio files that store a large amount of information, which is not identified or tagged to train a computer learning algorithm directly. The tags or the way to assign to the audio file a relationship with the bird's

Journal of Theoretical and Applied Information Technology
31st August 2021. Vol.99. No 16
© 2021 Little Lion Scientific
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

melody is manually, by a person in charge of determining which species the captured sound corresponds to. Although this activity makes processing a single audio file very time consuming, strategies have been designed to reduce the search time of the person in charge [12-16]. Basically, these strategies digitally filter the audio signal, remove ambient noise, extract and signal tones that are in a previously established frequency range, as shown in Fig. 1.



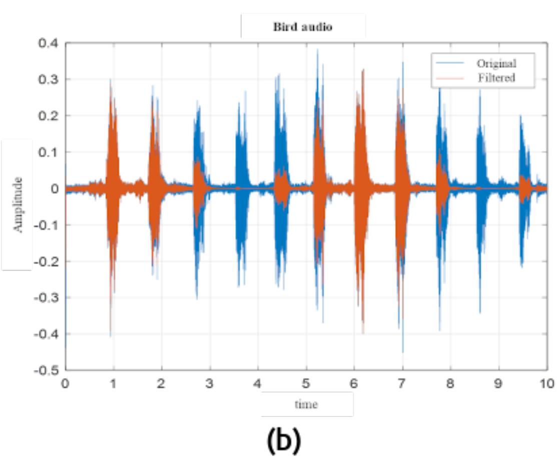


Figure 1: General scheme of an audio segment labelling technique; a) General scheme, b) Filtered audio signal

Although, other techniques have tried to substitute human intervention during the interpretation of information, these techniques require training that is done from the information previously selected and labeled by a user. Therefore, the reduction of human intervention in the face of information classification processes is still a developing issue [16].

The techniques that try to reduce human intervention base their operation on computational learning algorithms, which require a group of data to build models that allow the machine to interpret the available information. These data sets are databases with records that contain detailed information on the attributes or variables that are attempted to be predicted from others (predictors). However, not all the techniques implemented require the selection of input parameters, for example, the identification of patterns using unsupervised learning algorithms is a process that consists of grouping the information according to some selection parameters, which has allowed the identification of the characteristic song of some bird species [14, 16-17].

In this work, an implementation was made with a supervised learning algorithm based on a Deep Learning Neural Network (DLNN), which requires specifying the input and output parameters. A DLNN is a robust version of a traditional neural network that aims to represent a volume using a model based on biological neural synapse. The models generated by a DLNN are regression or classification models, where the regression models are like mathematical equations with variable coefficients and the classification models group the information according to its characteristics. In both cases, the user does not know the form of the model, since it is an object that is given an input to produce an output [18-22].

Although the DLNN model is unknown to the user, the topology or mechanism of connection between neurons to generate the model depends on some quantitative parameters such as the input and output attributes, the neurons and connections between them, the form of the activation function and the training algorithm. On the one hand, the number of neurons and the input and output attributes are defined by the user before the DLNN training, considering that a larger number of neurons increases the time of construction of the model and the level of accuracy. On the other hand, the activation function limits the range of output values for each neuron, since the weight assigned during training is a variable that can increase exponentially [23-25].

Currently, there is no mechanism for determining the number of neurons in a DLNN, so testing in various network configurations is suggested [26-28]. Because, each configuration assigns a distinctive or characteristic weight to each neuron, which is adjusted with the activation function and assigned with the training algorithm. This algorithm

Journal of Theoretical and Applied Information Technology
31st August 2021. Vol.99. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

takes from the training data set a part to validate the response provided by the model during its execution, i.e., in each iteration the algorithm checks the error level between the training data and those provided by the model when modifying the weights of the network [19].

In this work a DLNN was implemented with the following characteristics: one input, 2800 neurons, seventy hidden layers, the initial weights of each neuron are assigned with a function of random number generation with normal distribution, a function of sigmoid activation and a training function based on the descending gradient that corrects the margin of error with a measure of similarity between the training data and those provided by the model using the cosine function (Eq. 1).

$$\alpha = cos\left(\theta\right) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \quad (1)$$

Basically, the similarity measure states that the training and output data sets of the model are vectors (A and B) and attempts to find an angle between them (α of (1)), which varies between -1 and 1 assuming that as this value approaches zero the vectors reduce their similarity (*n* is the number of individual components of each vector).

DLNN training was conducted with a set of 360 song samples from 12 different bird species available in a repository (30 songs for each species, 10 seconds each) [11]. This set of samples was arranged in the form of a list, see Fig. 2, where each of its components is filtered, segmented, and normalized as shown in Fig. 3, if any training sample cannot be segmented the component has a value of zero by default. Each record of the attribute is assigned a bird species that is coded with a number:

- 0=Default value
- 1=Common Columbus
- 2=Olive Rufous Bush
- 3=Eagle Frigate
- 4=Short Swan
- 5=Minor Frigate
- 6=Melanoleucous Microcarb
- 7=Microcarbo coronatus
- 8=Galbula albirostris
- 9=Galbula ruficauda

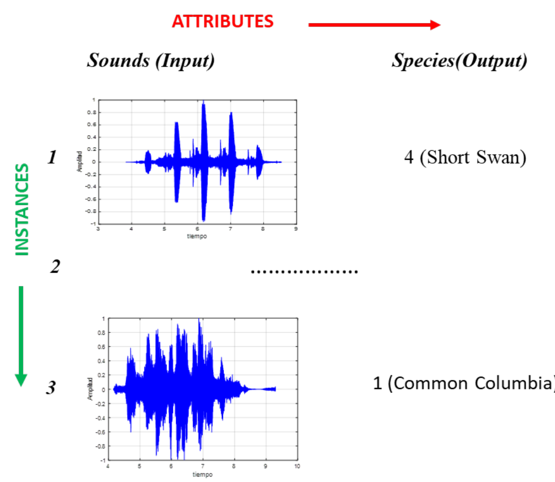
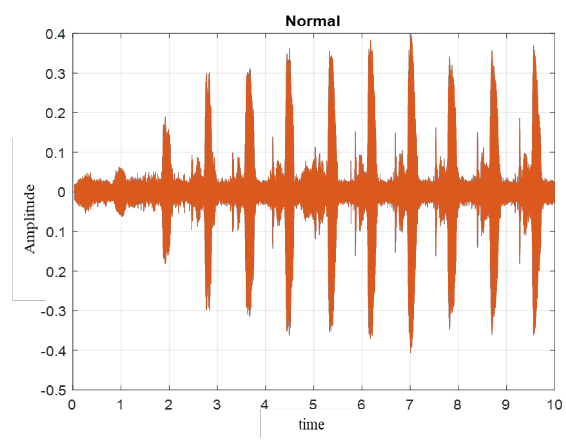
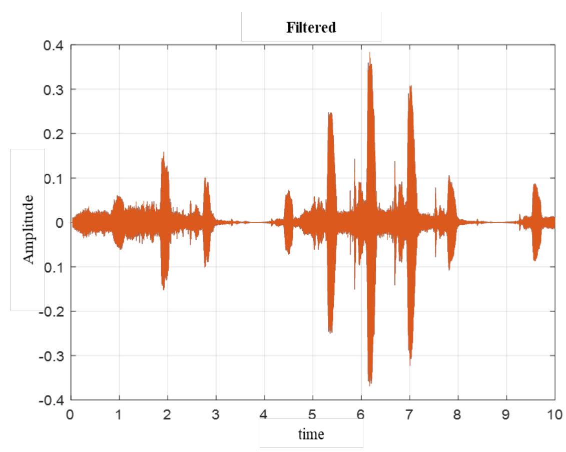


Figure 2: Segment of the database used



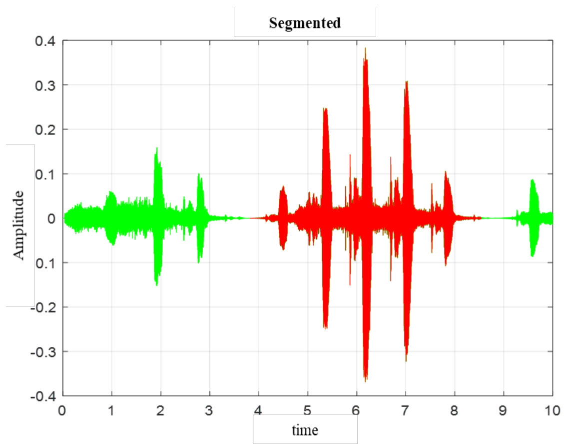
(a)



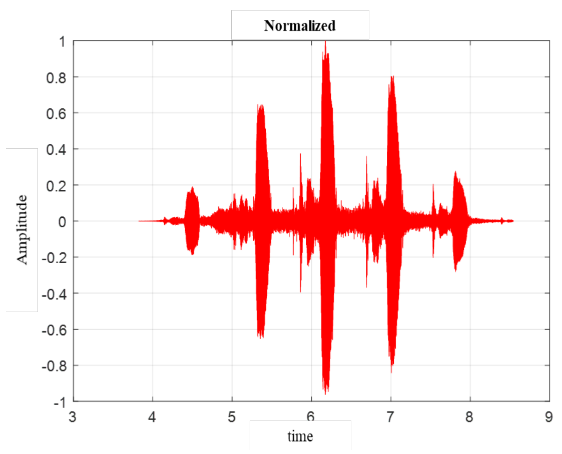
(b)

Journal of Theoretical and Applied Information Technology
31st August 2021. Vol.99. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



(c)



(d)

Figure 3: Extraction of audio signal characteristics; a) Original sound, b) Filtered sound, c) Segmentation, d) Standardization

As can be seen, the generation of each instance of the input attribute depends on pre-processing to extract the region of interest [29]. This preprocessing allows the reduction of irrelevant information not related to sound characteristics while reducing the processing complexity and facilitating the work of the neural network. In this case to the original file a high-pass filter is applied with a cutoff frequency in 300 Hz that removes the noise from the environment, then a band-pass filter removes the periodic signals outside the frequency ranges between 1000 and 7000 Hz (range of sounds produced by birds). The resulting part is stored in a variable to build the training database. This process is repeated with each of the entries, which made it possible to construct a dataset-specific to the study problem.

The detail of this two-stage filter can be seen in Fig. 4. The signal is digitized and applied to a high-pass filter to reduce noise, and the result is injected into the band-pass filter. Finally, the filtered signal is analyzed and stored.

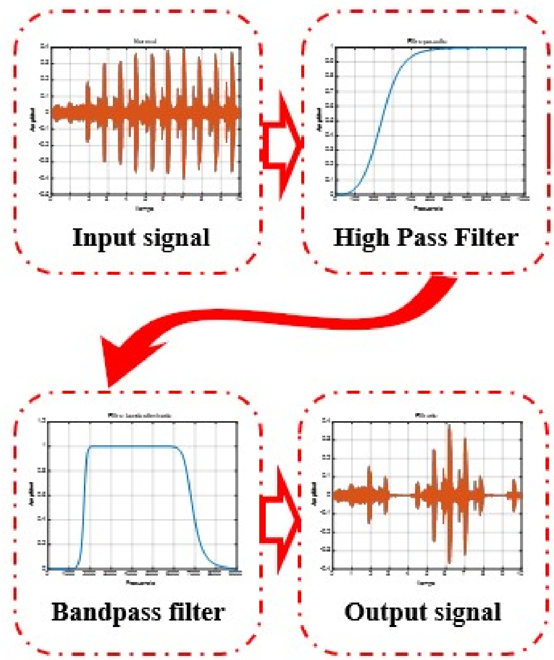


Figure 4: Characteristics of the filtering done to the audio signal

Finally, when building the database, the DLNN training was performed with 70% of the available information and the remaining 30% was used as validation data to corroborate the model performance. The validation data are completely unknown for the trained neural model, and during training, we sought to randomly mix each input signal to reduce the possibility of bias.

The performance metrics were mainly applied to the results of the neural models with the validation data; however, each training process was followed up by checking the behavior of the metrics with both the training data and the validation data. This analysis made it possible to determine abnormal and undesirable behaviors of the models, such as over-fitting. In such cases, the solution chosen was to adjust the neural network architecture instead of trying to improve its behavior based on the validation data, which allowed the selection of topologies with high performance and high fitting capacity. The algorithm used is shown in Fig. 5 and complemented with the information presented in the following section.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Algorithm 1. Operation of the DLNN Training Algorithm

```
Function Create_DLNN ()
 Arrangement 1 ← Import sounds available in the root directory.
  For i < length (Arrangement 1) do
       If Arrangement 1 [i] ¡= null then
          Database [i] ← Filter sounds (Arrangement 1)
       Else
          Database [i] ← Fill in the register with zeros ()
  Data Base ← Filter available sounds (Database)
  Input Attributes ← Segmenting available sounds (Database)
  Output attribute ← Sound file name (Database)
  DN←Define DLNN
  Training data← [Input Attributes, Output Attributes]
  Training data← Training Data (Select 70%)
  Validation data← Training Data (Select 30%)
  DN←Train DN (Training Data)
  DN←Validate DN (Validation data)
  Export DN

Main Function ()
  DN ← Import trained model
  SN ← Read sound from file
  SN ← Filter SN
  SN ← SN Segmenting
  S1 ← Evaluate using the DN(SN)
  Publish ("The species is:" S1)
```

Figure 5: Operation of the DLNN Training Algorithm

3. IMPLEMENTATION

The application presented in this work was made using the KERAS, TENSORFLOW and OPENCV 3.4.0 libraries of PYTHON 3.6 in the Anaconda interpreter in its version 3.8 of SPYDER and was tested in a computer with an Intel® inside CORE^TM i3 processor and 8 Gb of RAM memory. All training was performed individually on this machine, continuously monitoring the resource consumption and the time required in each case. This information will be used in future developments of this research under resource optimization considerations of the scheme.

In addition, four implementations of Algorithm 1 (Fig. 5) were made with different configurations of the DLNN (see Table 1) to choose among them the best one (reported in the previous numeral). In all cases, a selection of records from the database was made for training and validation in a stochastic way, whose results are presented in the following section.

4. RESULTS AND DISCUSSION

As mentioned, four different configurations of the DLNN were made and trained with 70% of the total records in the database and validated with the remaining 30%. During the validation process the graph in Fig. 6 was constructed, which groups the curves that present the reduction of the margin of error between the expected value (species of the bird taken from the database) and the given value (model output) during the training of the network. To validate the performance of the models, other metrics were also calculated for each case, including Precision, Recall, F1-score, confusion matrix, and ROC curve, the latter two focused on evaluating the categorization capacity of each of the different models.

Journal of Theoretical and Applied Information Technology
31st August 2021. Vol.99. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: DLNN test settings

DESCRIPTION	*DLNN CONFIGURATIONS*			
	DLNN 1	*DLNN 2*	*DLNN 3*	*DLNN 4*
Number of neurons	2800	1500	3500	3500
Trigger function	Sigmoid	Hyperbolic Tangent	Exponential	Sigmoid
Algorithm to assign initial values to the weights	Random with normal distribution	Random with uniform distribution	Zeros	Random with normal distribution
Number of hidden layers	70	70	70	70
Optimisation algorithm	Nadam	Adagrad	Adagrad	Nadam
Error estimation strategy	Descending gradient	Half-square error	Half-square error	Descending gradient

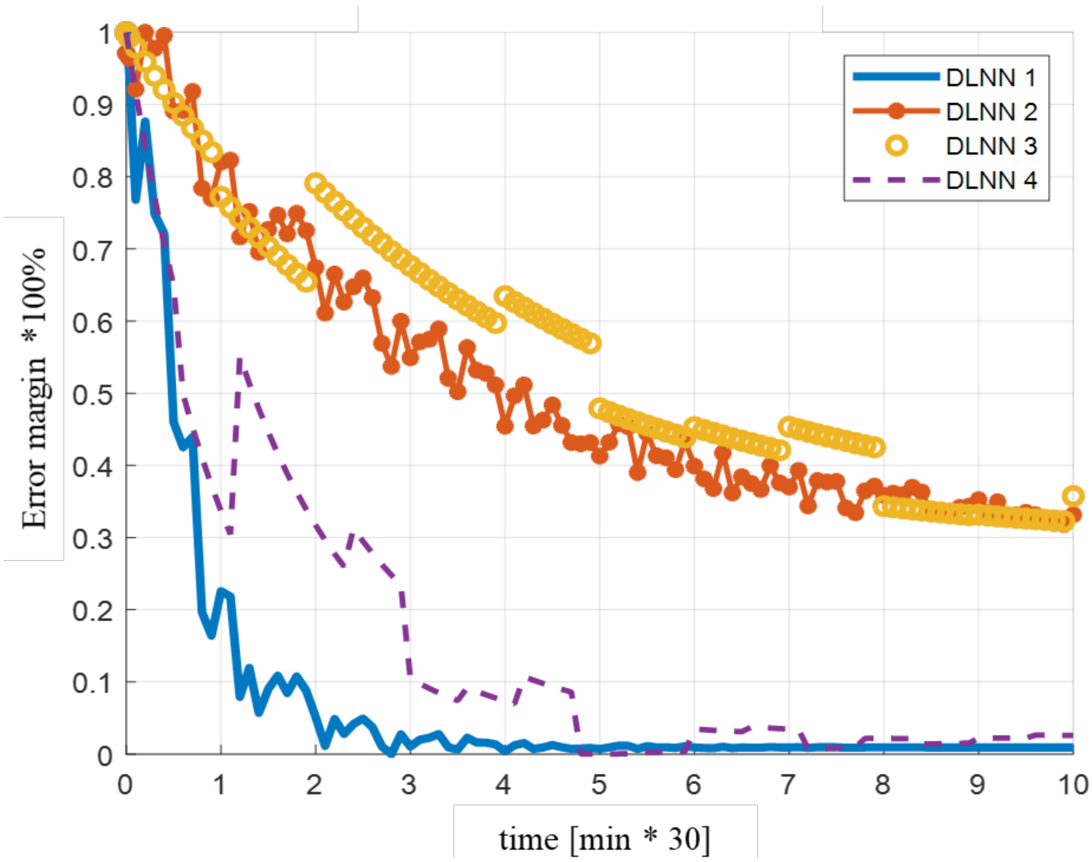


Figure 6: Performance during DLNN training in its different configurations

Once the training of the nets was completed, another experiment was carried out consisting of selecting 50 random songs from the training database and 60 songs (5 per species with intervals of duration between 10 and 60 seconds) that were not used during the training or validation, to measure the margin of error in each configuration and determine whether it is possible for the proposed technique to predict from other sound files (see Table 2). This research will continue seeking to optimize the performance of the current models, both in neural network structure and in digital signal processing to reduce operation times and increase the categorization capacity of the scheme.

6. CONCLUSIONS

Fig. 3 shows that it is possible to extract information from audio signals without a trained classifier, i.e., only digital filters tuned within the frequency spectrum of the bird's song eliminate ambient noise and it is possible to extract the base melody of the bird for further training of the DLNN. Although this is not a 100% effective procedure, since it does not eliminate the noise from the environment in its entirety, it is versatile and efficient enough to reduce the segmentation time of an audio signal compared to a manual (the listener segments the audio) or hybrid (the listener segments the audio according to the information given by the machine) procedure.

Table 2: Number of edges identified by the DLNN

	CONFIGURATION			
	DLNN 1	**DLNN 2**	**DLNN 3**	**DLNN 4**
KNOWN SONGS				
PREDICTED	50	25	19	45
NOT PREDICTED	0	25	31	5
TOTAL	**50**	**50**	**50**	**50**
UNKNOWN SONGS				
PREDICTED	38	10	2	25
NOT PREDICTED	22	50	58	35
TOTAL	**60**	**60**	**60**	**60**

Fig. 4 presents a segment of the database used for the training of the DLNN in its different configurations, whose input attribute is an array that stores multiple conditioned audio files. In other words, DLNNs support multi-dimensional arrays as input parameters packaged as dimensionality one arrays, which reduces their implementation and design time compared to other categorical classification techniques such as clustering or decision trees. This functional advantage allowed the realization of experiments with four different DLNN configurations (Fig. 6) of which DLNN 1 was the one that had a smaller convergence time and error margin than the other three configurations.

Table 2 presents the results obtained when testing DLNNs with sound files of different characteristics, which allows two characteristics of DLNNs to be highlighted. On the one hand, if the DLNNs with configurations such as 2 and 3 shown in Table 1 have a margin of error greater than 40% (Figure 5) it is possible that with a longer training time they will converge to a satisfactory result. On the other hand, the DLNN with configurations 1 and 4 shown in Table 1 predict different information than the one projected with the training data with an average margin of error lower than 5%, which indicates that it is possible that this technique finds bird species in files with a length of more than 10 seconds, with different recording intervals between them and with more than one melody contained in the audio file.

8. ACKNOWLEDGMENT

This work was supported by the Universidad Distrital Francisco José de Caldas, in part through CIDC, and partly by the Facultad Tecnológica. The views expressed in this paper are not necessarily endorsed by Universidad Distrital. The authors thank the research group ARMOS for the evaluation carried out on prototypes of ideas and strategies.

REFRENCES

[1] Q. Wang, Y. An, Y. Li and H. Wang, "Set-based Noise Elimination for Is-a Relations in a Large-Scale Lexical Taxonomy," 2019 IEEE International Conference on Power Data Science (ICPDS), Taizhou, China, pp. 101-104, 2019.

[2] BirdLife International, "El Estado de conservación de las aves del mundo: tomando el pulso de nuestro planeta." Birdlife International. Cambridge, UK, 2018.

[3] M. Raghuram, et al., "Bird classification based on their sound patterns." International journal of speech technology, vol. 19, no 4, p. 791-804, 2016.

[4] P. Donald, et al., "Important Bird and Biodiversity Areas (IBAs): the development and characteristics of a global inventory of key sites

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

for biodiversity." Bird Conservation International, vol. 29, no 2, p. 177-198, 2019.

[5] D. Stowell, E. Benetos and L. F. Gill, "On-Bird Sound Recordings: Automatic Acoustic Recognition of Activities and Contexts," in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 25, no. 6, pp. 1193-1206, 2017.

[6] Z. Zhao, et al., "Automated bird acoustic event detection and robust species classification." Ecological Informatics, vol. 39, p. 99-108, 2017.

[7] A. Muminov, Y. C. Jeon, D. Na, C. Lee and H. S. Jeon, "Development of a solar powered bird repeller system with effective bird scarer sounds," 2017 International Conference on Information Science and Communications Technologies (ICISCT), Tashkent, pp. 1-4, 2017.

[8] Y. Chen, Y. Dai and Y. Chen, "Design and Implementation of Automatic Bird-blocking Network in Airport Intelligent Bird-repelling System," 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chengdu, China, pp. 2511-2515, 2019.

[9] Y. Chen, Z. Liu, Y. Chen and Y. Liu, "Design of Gateway in Airport Intelligent Bird-repelling System," 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chengdu, China, pp. 2060-2064, 2019.

[10] Jutglar, F., Mètode, R., Mètode, R., Ligero, S., Mètode, R. and Mateu, A., "El canto de los pájaros". Revista Mètode, 2018.

[11] Naturalis Biodiversity Center, Xeno-canto.org is powered by the Xeno-canto Foundation and Naturalis Biodiversity Center, Dataset, 2020.

[12] K. Qian, Z. Zhang, F. Ringeval and B. Schuller, "Bird sounds classification by large scale acoustic features and extreme learning machine," 2015 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Orlando, FL, pp. 1317-1321, 2015.

[13] D. Chakraborty, P. Mukker, P. Rajan and A. D. Dileep, "Bird Call Identification Using Dynamic Kernel Based Support Vector Machines and Deep Neural Networks," 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA), Anaheim, CA, pp. 280-285, 2016.

[14] R. Narasimhan and R. Raich, "Simultaneous segmentation and classification of bird song using CNN," 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 146-150, 2017.

[15] N. Bold, C. Zhang and T. Akashi, "Bird Species Classification with Audio-Visual Data using CNN and Multiple Kernel Learning," 2019 International Conference on Cyberworlds (CW), Kyoto, Japan, pp. 85-88. 2019.

[16] H. Barmatz, et al., "A Method for Automatic Segmentation and Parameter Estimation of Bird Vocalizations," 2019 International Conference on Systems, Signals and Image Processing (IWSSIP), pp. 211-216, 2019.

[17] J. Salamon, et al., "Fusing shallow and deep learning for bioacoustic bird species classification." 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 141-145, 2017

[18] R. Feng, C. Leung, J. Sum and Y. Xiao, "Properties and Performance of Imperfect Dual Neural Network-Based k WTA Networks," in IEEE Transactions on Neural Networks and Learning Systems, vol. 26, no. 9, pp. 2188-2193, 2015.

[19] A. B. Adege et al., "Applying Deep Neural Network (DNN) for large-scale indoor localiza-tion using feed-forward neural network (FFNN) algorithm," 2018 IEEE International Con-ference on Applied System Invention (ICASI), Chiba, pp. 814-817, 2018.

[20] K. Rahul Vigneswaran, R. Vinayakumar, K. Soman and P. Poornachandran, "Evaluating Shallow and Deep Neural Networks for Network Intrusion Detection Systems in Cyber Se-curity," 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Bangalore, pp. 1-6, 2018.

[21] D. Ulinic, J. Casas. "Why neural networks and deep learning are the future in machine learning", B. Eng. thesis, Universitat Autónoma de Barcelona, Spain, Mar. 2018.

[22] M. A. Abu et al., "A study on Image Classification based on Deep Learning and TensorFlow," International Journal of Engineering Research and Technology, vol. 12, no. 4, pp. 563-569, 2019.

[23] Sugiarti et al., "An Artificial Neural Network Approach for Detecting Skin Cancer," TELKOMNIKA Telecommunication Computing Electronics and Control, vol. 17, no. 2, pp. 788-793, 2019.

[24] D. Zhang, X. Han and C. Deng, "Review on the research and practice of deep learning and reinforcement learning in smart grids," CSEE

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Journal of Power and Energy Systems, vol. 4, no. 3, pp. 362-370, 2018.

[25] M. Lasseck, "Acoustic bird detection with deep convolutional neural networks." Proceedings of the Detection and Classification of Acoustic Scenes and Events 2018 Workshop (DCASE2018), pp. 143-147, 2018.

[26] F. Martínez, F. Martínez and E. Jacinto, "Performance evaluation of the NASNet convolutional network in the automatic identification of COVID-19," International Journal on Advanced Science, Engineering and Information Technology (IJASEIT), vol. 10, no. 2, pp. 662-667, 2020.

[27] F. Martínez and H. Montiel, "Low cost, high performance fuel cell energy conditioning system controlled by neural network," TELKOMNIKA, vol. 18, no. 6, pp. 3116-3122, 2020.

[28] F. Martínez, C. hernández and A. Rendón, "Identifier of human emotions based on convolutional neural network for assistant robot," TELKOMNIKA, vol. 18, no. 3, pp. 1499-1504, 2020.

[29] A. Rendón, "Operational amplifier performance practices in linear applications," Tekhnê, vol. 16, no. 1, pp. 57-68, 2019.