

Multi-class Classification of Impulse and Non-impulse Sounds Using Deep Convolutional Neural Network (DCNN)

Adebayo Abayomi-Alli[1(✉)], Olusola Abayomi-Alli[2], Jeffrey Vipperman[3], Modupe Odusami[2], and Sanjay Misra[2]

[1] Department of Computer Science, Federal University of Agriculture, Abeokuta, Nigeria
abayomiallia@funaab.edu.ng

[2] Department of Electrical and Information Engineering, Covenant University, Ota, Nigeria
{olusola.abayomi-alli,modupe.odusami,
sanjay.misra}@covenantuniversity.edu.ng

[3] Department of Mechanical Engineering, University of Pittsburgh, Pittsburgh, USA
jsv@pitt.edu

Abstract. Differentiating between military sounds can be quite tasking with high false detection rate. These sounds can either be impulse sounds (sounds released from the military weapons) or non-impulse sounds (sound released from other sources) thus causing public disturbance and unnecessary panic. This paper utilizes Deep Convolutional Neural Network (DCNN) classifier to detect military impulse and non-impulse sounds and also incorporates Adam algorithm for optimal classification. DCNN was utilized in this study based on its network embedded multiple hidden layers (non-linear) which can learn the very complicated relationship between the input data and require output. The dataset used in this study consist of six sound types with a total number of 37,464 datasets which was partitioned into training (67%) and testing (33%). The performance of the proposed classifier was evaluated based on the following metrics: True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), Precision, Matthews Correlation Coefficient (MCC), and Accuracy. The experimental result shows that DCNN classifier gave an optimal accuracy for the Machine gun, Wind, Thunder, Blast, Vehicle, and Aircraft sounds types as 97.43%, 96.98%, 95.16%, 95.13%, 88.83%, and 87% respectively. The average classification error rate for the six sound types was 6.57% which signifies that DCNN is a promising classifier.

Keywords: Military sound · DCNN · Impulse and non-impulse sounds · ADAM algorithm

1 Introduction

Impulse noise is generated during military installation and this noise propagates to the surrounding communities thereby resulting in public annoyance [1, 2]. This type of noise can also be characterized by its high-pressure level in a very short duration [3].

© Springer Nature Switzerland AG 2019
S. Misra et al. (Eds.): ICCSA 2019, LNCS 11623, pp. 359–371, 2019.
https://doi.org/10.1007/978-3-030-24308-1_30

Blast noise typically refers to as impulse noise that generated from military bases [4]. Using instrument attack such as weapons and mortal strength to protect and guide everyone interest is the term that described military. The military weapons are machine gun, bomb blast, tank firing, suicide bomber, AK47 assault rifle, double barrel shotgun firing, and so on [5]. The goal of powerful offensive weapons used by the military is to overpower the people fighting against the country by long range and highly accurate mortal strikes. Non-impulse sounds are other sources of sounds that are not from a military weapon such as the cry of a baby, wind, aircraft, and so on. The annoyance caused by impulse and non-impulse noise is important in making a stable task to follow up thus, record sound events to provide additional evidence of any damage claims [6].

Several research works have been done in measuring and analyzing weapon noise such as gunfire noise detection system but there are still problems in classifying military impulse noise and other noise sources such as challenges of severe overlap of Interquartile Range (IQR) between those noises due to wind introduction [7]. Figure 1 shows the diagrammatic representation of a noise classification system.

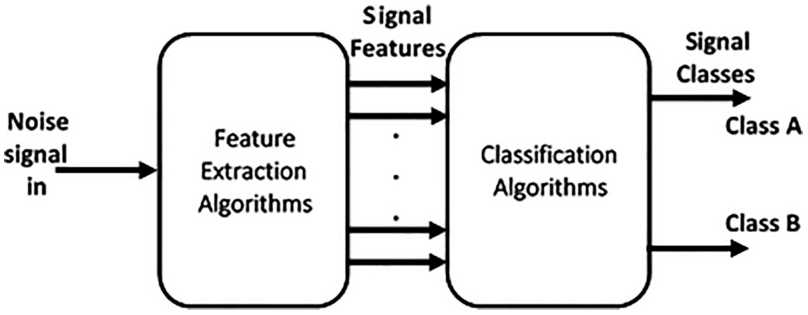

Fig. 1. A diagrammatic representation of a noise classification system.

Military sounds from larger weapons have a much deeper sound than sounds from lighter ones. This suggests that there might be a discernible difference in frequencies which Spectrogram analysis will be able to quantify [8]. False detection mostly occurs when classifying a waveform either impulse noise or non-impulse noise such as wind.

According to [9], it is very useful to have information not only about direction and distance but also about specific weapon category and the sound event it could belong to. Moreover, this can help during an investigation of crime incidents in common life where sound evidence is available.

Several techniques have been used to classify military impulse sounds and non-impulse sound like Bayesian classifier, Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), Fast Random classifier, Artificial Neural Network Classifier. In this study, Deep Convolutional Neural Network classifier was applied to classify both military impulse and non-impulse sounds. The rest of the paper is organized as follows: Sect. 2 gave a detailed literature review and existing methodology deployed in related studies while Sect. 3 describes the proposed methodology. The results and discussion are presented in Sect. 4 and the paper concludes with recommendations in Sect. 5.

2 Literature Review

This section gave a comprehensive review of existing studies based on Machine Learning methods and deep convolutional neural network in sound classification.

Machine Learning is a field emerged from Artificial Intelligence which has gained vast application in several research areas ranging from industry to basic science [10]. Its primary aim is to make machines exhibit or mimic human kind of intelligence for the purpose of decision making, classification, detection, etc. The application of Machine learning varies from supervised learning, unsupervised learning, reinforcement learning, etc. Literature has shown that the majority of the method used in identifying military impulse noise are ML ranging from ANN, SVM, KNN classifier, etc. [11].

Deep Learning is a subarea of Machine learning which is based on algorithms inspired by architectural structure and function of the human brain known as Artificial Neural Network. Convolutional Neural Network (CNN) is a specialized NN used in grid-like topology using multiple filters with fewer connections and parameter thus easier to train [12, 13].

Yang and Chen presented a review of Machine recognition of music emotion in [14]. The study gave a comprehensive study of existing methods and the proposed solutions for recognizing music emotion. [9] identified gunshots sound using spectral characteristics by normalizing the amplitude and the frequency of the sample collected, and converted the signal from time domain to frequency domain through Fourier transform by extracting the features needed. MATLAB was used for the implementation using Neural Network toolbox and C programming language. [15] classified sound of frogs based on their species using three features: signal bandwidth, threshold-crossing rate, and spectral centroid. Frog sound was segmented into syllables before classifying the sound using SVM and Kth Nearest Neighboring (KNN) classifier. [16] however, developed an accurate method for noise classification with event detection of lower peak levels down to 100 dB (decibel) using all the ANN structures and proved that nonlinear capabilities of ANN give an edge over a linear classifier. Time and frequency domain features were used for the classification. [7] developed an ANN based classifier for 330 and 660 military impulse and non-impulse noise, respectively using time domain metrics and custom frequency domain metrics for ANN structure selection. The ANN structures are: SVM with radial basis function, SOM, MLP, and Least Square Classifier. The output of [7] proved that time domain metrics (kurtosis and crest factor) were good in classifying impulse noise. Military aircraft sound was classified by [17] using neural network and compact features vector. ANN method was introduced for aircraft engine signal classification, the ANN technique involved extracting a compact feature from the sound using Frequency Domain Metrics (FDM) as a method of extraction. FDM for the extractions are Spectral Centroid and Signal Bandwidth. [18] employed three architectures: CNN, ANN and Softmax regression. 480 samples of sounds were captured at 240 bmp for two minutes from 13 objects using drum kit and guitar. The three architectures failed to achieve accuracy above 20% on the latter representation after 500 iterations. However, CNN and ANN obtained accuracy above 80% using the frequency-space represented data. Softmax

regression failed to successfully classify the data while CNN achieves an accuracy of over 97%. [19] applied different ANN structures, Self Organizing Map (SOM), MLP, image recognition and SVM for sound classification using feature extraction method (time domain and frequency domain metrics). MLP performed most accurate among all the ANN structures.

Cakir applied multilabel Deep Neural Network (DNN) in [20] for real-time detection of multiple recorded sound events. Kumar and Raj applied deep CNN on weakly labeled web data for audio event recognition [21]. The approach emphasized temporal localization was able to train and test recordings of variable length accurately. Piczak proposed a sound event classification using DCNN classifier [22]. All sounds were inputted using Log-scaled Mel-spectrograms as feature extraction technique. The proposed system utilizes DCNN architecture consisting of a convolutional layer, Max-pooling layer, convolutional layer, fully connected layer, dropout layer and two fully connected layers. In conclusion, DCNN gave an accuracy of 73%. Bucci and Vipperman developed an ANN-based classifier for identifying military impulse noise [16]. The study was based on two time-domain and frequency-domain metrics which are kurtosis and crest factors with spectral slope and weighted square error. The study concluded that the system gave up to 100% accuracy during training and testing: The summary of reviewed related works is shown in Table 1.

Table 1. Overall summary of related works.

References	Objectives	Methodology	Contributions
[23]	Recognition of Musical Instrument using Distinctive Characteristics in Artificial Neural Networks	ANN	Effective recognition of musical instrument
[24]	Detection and recognition of gunshot impulsive sound using novel energy formula Recognition	Uses a window sample count and energy formula	MFCC gave better success rate when with High-frequency Amplitude
[25]	Detection of Sound Event in Urban Soundscape using Two-level Classification	Mel-Frequency Cepstral Coefficients (MFCCs) and NB, J48, Random Forest and ANN	Ability to identify/recognize sound events using prominent features
[26]	Development of an efficient acoustic detector for gunshots and glass breaking	Hidden Markov Models (HMMs) and a modified Viterbi decoding process	Easy support detection with low computational requirements
[27]	Improving feature learning for Urban Sound Classification using unsupervised learning	Spherical k-means algorithm	Reduced confusion between car horns, children and street music

(*continued*)

Table 1. (*continued*)

References	Objectives	Methodology	Contributions
[28]	Audio Signals classification using selected Machine Learning Algorithms	KNN and SVM algorithm using prosodic features	SVM outperforms KNN with reduced time complexity
[29]	Detection of environmental sound using Convolutional Neural Networks	CNN and Mel-Frequency Cepstral Coefficient (MFCC)	Proposed model outperforms other approaches to recognizing some specific classes
[30]	Aircraft classification using radar cross-section of long-range trajectories	Use Bistatic radar (BR) and cross-section (BRCS) profiles	Better classification result
[31]	Classification of aircraft and Estimation of acoustic impact using real-time take-off noise measurements	Two parallel feed-forward neural network combined with a weighted addition	Effective measurement of real-time noise for each take-off
[32]	Analyzing Machine Learning algorithms in music applications	Non-negative matrix factorization (NMF)	Evaluate the performance of LR to NMF in music applications
[33]	Detection of gunshot in a noisy environment	Hidden Markov Models working on LPC and MFCC	Low computational cost and robustness against noise
[34]	Automatic Recognition of Urban Environmental Sounds Events	Uses MPEG-7 audio low-level descriptors spectrum (centroid, spread and flatness)	MPEG-7 features improve the discrimination quality thus outperforming MFCCs

3 Methodology

This study uses a Deep learning technique to classify six different military impulse and non-impulse sounds [35]. The basic step required for military impulse sounds classification are Data collection, Feature extraction, and sounds classification.

3.1 Data Collection

The experiment was conducted on the dataset from six noise type military sound [35]. The dataset consists of six different sounds which we classified as impulse and non-impulse sound. These sound types comprise bomb-blast, wind, machine gun, aircraft, vehicle, and thunder. All sounds were extracted using 25 signal metrics as input with an overall of 37,464 records of sounds. The summary of data collected is depicted in Table 2.

Table 2. Summary of data collected.

S/N	Sound	Sum
1	Vehicle	6829
2	Aircraft	7107
3	Blast	14761
4	Wind	2817
5	Thunder	3991
6	Machine gun	1959

3.2 Feature Extraction

For better human interpretation of military impulse sounds and non-impulse sounds, is important to extract the features needed. This start from the initial set of data in order to derive values (features) intended to be formative with no redundancy. [19] extracting features required the following signal metrics of ANN:

i. Time domain metric: is the variation of amplitude of signals with time.
ii. Frequency domain metric: is how much signal lies in a frequency range.

Both metrics used were successful in the past considering fault check in the direct analysis of the input data [19], which is most likely the similar problem in identifying military impulse noise. Kurtosis and crest factor refer to as time domain metrics while weighted square error and spectral slope refer to frequency domain metrics. To give a good performance of sound classification, the input sounds need to be regularized for the purpose of avoiding overfitting.

Spectral Slope (m): is computed by creating a least-squares fit to a line as depicted in Eq. (1).

$$\mathrm{Y} = \mathrm{mx} + \mathrm{b}. \tag{1}$$

Where:
$y = \log_{10} PSD$ is the base-10 logarithm of the power spectral density (PSD), and $x = \log_{10} fx$ =log_10 ⟦f⟧ is the base-10 logarithm of frequency.

Weighted Square Error: This can be expressed as WSE:

$$WSE = \sum_{i=1}^{n} [y_i + y_l]^2 [f_{i+1}] - f_1] \tag{2}$$

$$y_i = \frac{\log_{10} PSD_i - \min[\log_{10} PSD]}{\max[\log_{10} PSD] - \min[\log_{10} PSD]} \tag{3}$$

Where:

y_i is the log10 (PSDi) of the ith frequency of data;
y_i the estimate of y_i from the linear curve fit;
f_i the log base 10 of the ith frequency;
n is the number of the input data.

$[y_i + y_l]^2$ allows WSE to remain positive and also reflects the total magnitude of the error. $[f_{i+1} - f_1]$ is to add greater weight to the error at the lower frequency bins. Distinguishing between military impulse noise and non-impulse noise is best with features which occurs at the lower end of the bandwidth in consideration.

Kurtosis and Crest Factors: When comparing wind noise and military impulse sounds, Crest factor slightly overlaps the IQR. However, Kurtosis has no IQR overlap with comparison of other noise sources and military impulse noise sources. Kurtosis is used for describing or estimating a distribution's peak level and frequency of extreme values, it can be computed as:

$$K = \frac{1}{\delta^4 T} \int_0^T (x - \mu)^4 dt \tag{4}$$

Where:

x refers to the signal;
δ is the variance of the signal;
μ is the mean acoustic pressure;
T is the time frame over which the kurtosis is measured [16].

Crest factor is the peak value of the waveform (PPK) divided by the Root Mean Squared Value (PRMS) of the signal and it is calculated as:

$$Crest\,factor = (peak\,value)/(rms\,value\,of\,currentwaveform) \tag{5}$$

3.3 DCNN Classifier

DCNN is a network embedded classifier with multiple hidden layers (non-linear) which can learn the complicated relationship between the input data and require output. This classifier is inspired by biological variant of MLs for classifying military impulse sound [36]. DCNN consist of three layers: Convolutional layer, pooling layer, and fully connected layer.

i. Convolutional layer: this layer is the first layer and core building block of DCNN that ensure the equality be-tween the input and output parameters performance. This layer helps the DCNN model to train faster, no matter the number of data. Without a convolutional layer no DCNN model.
ii. Pooling layer. This is the layer that must follow immediately after convolutional layer output, because the convolutional output is the pooling layer output which helps to simplify the information further.
iii. Fully connected layer. This layer consists of all the input from the beginning of the layer. After each layer, activation function would be applied to give the model power to be more flexible to arbitrary relations. However, there are various activation functions, but Rectified Lineal activation functions (RELu) would be applied with its mathematical expression given in Equations below.

$$y = \frac{1}{(1 + e^{net})} \tag{7}$$

Figure 2 shows the dataflow diagram for the proposed DCNN model..
The hyperbolic target sigmoidal activation function is represented as:

$$y = \frac{e^{net} - e^{-net}}{e^{net} + e^{-net}} \tag{8}$$

Where: y is the output activated, and the net is the sum of the input layer without activation function.

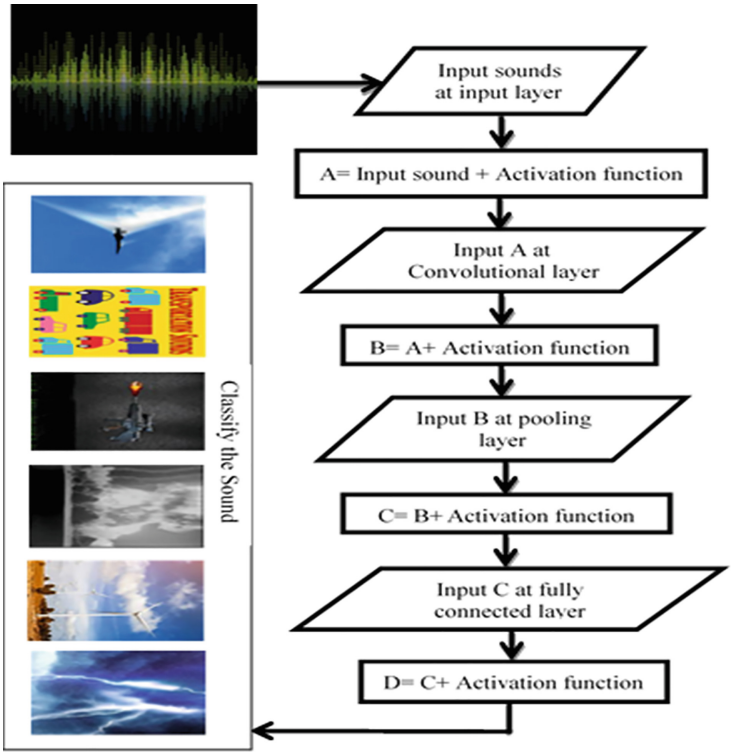

Fig. 2. Flow diagram for the proposed DCNN model.

3.4 ADAM (Adaptive Moment) Algorithm

Adam is an optimizer that can be used to solve problems with larger and noisy parameters in the field of deep learning. The optimizer was implemented using tested default settings for machine learning problems which are $\propto = 0.002$, $\beta_1 = 0.9$, and

β_2 = 0.999. With β_1^t denote β_1 to power of t. The learning rate with the bias-correction term for the first moment of ADAM is $\frac{\propto}{1-\beta_1^t}$. Procedure for the ADAM algorithm is given as:

Input: {Stepsize $\propto$; Exponential decay rates β_1, β_2, Stochastic objective function $f()$; Parameter vector θ_0}
Start;
For all β_1, $\beta_2 \in [0,1]$
Let $f(\theta)$: Stochastic objective function with parameters θ
For θ_0 is the initial parameter vector
$m_o \leftarrow 0$ (Initialize 1st-moment vector)
$u_0 \leftarrow 0$ (Initialize the exponentially weighted infinity norm)
$t \leftarrow 0$ (Initialize timestamp)
While $\theta_t$converged do
{
$t \leftarrow t + 1$
$g_t \leftarrow \nabla_0 f_t(\theta_{t-1})$ (Get gradients w.r.t. stochastic objective at timestep t)
$m_t \leftarrow \beta_1 . m_{t-1} + (1 - \beta_1) . g_t$(Update biased first moment estimate)
$u_t \leftarrow \max(\beta_2 . u_{t-1})$,
$absolute\ g_t$ (Update the exponentially weighted infinity norm)
$\theta_t \leftarrow \theta_{t-1} - \left(\frac{\propto}{1-\beta_1^t}\right) . m_t / u_t$ (Update parameters)
end while
}
return θ_t(Resulting parameters)
End;

4 Results and Discussion

A total record of 37,464 impulse and non-impulse military sounds was used to train and test the developed DCNN classifier. The data was partitioned as training (67%) and testing (33%) datasets consisting of 25,101 and 12,363 sound records, respectively. The results obtained are presented in the sub-sections below.

4.1 Performance Evaluation

The DCNN classifier was evaluated using the confusion matrix containing True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN), Precision, Matthews Correlation Coefficient (MCC), Accuracy (Acc), Receiver Operating

Characteristics curve (ROC) and the Area Under the ROC Curve (AUC). The order of partitioned for each sound type is depicted in Table 3.

Table 3. Partitioned dataset for each sound type.

Target	Sound	Training	Testing
0	Aircraft	4272	2557
1	Blast	2373	4734
2	Machine gun	14188	573
3	Thunder	1662	1155
4	Vehicle	1456	2535
5	Wind	1150	809
Total		25101	12363

4.2 DCNN Model Performance Result

The experimental result obtained for the performance of DCNN for the six classes of sound types is depicted in Table 4. Table 4 gave an analysis of the number of the predicted results against the actual result. The table shows the true values for the six classes of sound type with vales of TP, TN, FP, and FN.

Table 4. Positives and negative detection in DCNN.

Sound	TP	TN	FP	FN
Aircraft	1625	9132	932	674
Blast	4508	7253	226	376
Machine gun	453	11593	120	197
Thunder	921	10844	234	364
Vehicle	1725	9258	810	570
Wind	693	11297	116	257

The positive and negative detection for DCNN is shown in Table 4 while the overall accuracy of the six classes of sounds based on the precision, MCC and Accuracy is shown in Table 5 with the DCNN classifier returning best accuracy result for Machine gun, Wind and Thunder as 97.43%, 96.98%, and 95.16%, respectively.

Table 5. Positives and negative detection in DCNN.

Sound	Precision	MCC	Acc.	Error rate (%)
Aircraft	63.55	59.00	87.00	12.99
Blast	95.22	89.78	95.13	4.87
Machine gun	79.05	72.89	97.43	2.56
Thunder	79.74	72.94	95.16	4.84
Vehicle	68.04	64.63	88.83	11.16
Wind	85.66	77.47	96.98	3.02

The Table 5 further shows that the classification error rate for Machine gun as the lowest with 2.56% followed by wind with 3.02% thunder with 4.84%. This result depicts that DCNN classifier based on Machine gun, wind, thunder, and blast is quite encouraging as its error rate is still within the acceptable and standard rate.

5 Conclusion

This study was based on a developed DCNN model, a variant of MLP was used to classify six categories of sounds (military impulse and non-military impulse). The experimental result showed that DCNN model gave an optimal accuracy when classifying Machine gun, Wind and Thunder sounds types as 97.43%, 96.98%, and 95.16%, respectively. Classification of Aircraft and Vehicle sound type was lower with 87.0% and 88.83%, respectively. However, the average classification error rate for the six sound types was 6.57% which shows that the detection rate of DCNN signifies a promising classifier. We plan to compare the obtained result with pervious implementations of ANN with varying numbers of inputs features e.g. 4, 8 and 25.

Acknowledgments. The Authors appreciate the Covenant University Centre for Research, Innovation and Discovery for their support. In addition, we appreciate the Sound, Systems and Structures Laboratory, Swanson School of Engineering, University of Pittsburg, Pittsburg for providing the dataset.

References

1. Schomer, P.D., Robert, D.: Neathammer, Community Reaction to Impulsive Noise: A Final 10-Year Research Summary (U.S. Army Construction Engineering Research Laboratories Technical Report, N-167) (1985)
2. Rhudy, M.B.: Real-time implementation of a military impulse noise classifier. Master thesis, Department of Mechanical Engineering, University of Pittsburg, USA (2009)
3. Nakashima, A., Farinaccio, R.: Review of weapon noise measurement and damage risk criteria: considerations for auditory protection and performance. Mil. Med. **180**(4), 402–408 (2015)
4. Bruce, E., Tomasz, R.: High-Level Impulse Sound and Human Hearing, Standard Physiology, Quantization: Army research laboratory (ARL-TR-6017) (2012)
5. Patrick, B., Peter, S.: Noises and Sounds John Hopkin Bloomberg School and Public Health, vol. 6, pp. 1–48 (2006)
6. Zhang, X.T., Meyer, B., Skoie, D.: Anonymous. Office of Economic Adjustment, Office of Assistant Secretary of Defense, and Economic Security. Joint Land Use Study. Office of Economic Adjustment, DUSD(I&E), Suite 200, 400 Army Navy Drive, Arlington, VA 22202-2884 (703), pp. 604–620 (1993)
7. Bucci, B.A.: Development of artificial neural network-based classifiers to identify military impulse noise. Master's thesis, Mechanical Engineering, University of Pittsburgh (2007)
8. Martin, J.: Support vector machine classification of gunshots. Ph.D. Paper, Duke University, pp. 1–9 (2007)

9. Milan, N., VojTech, K., Petr, D.: Neural network classification of gunshots using spectral characteristics. Department of Electronics and Measurement: in proceeding recent researches in automatic control, pp. 262–267 (2011)
10. Das, S., Dey, A., Pal, A., Roy, N.: Applications of artificial intelligence in machine learning: review and prospect. Int. J. Comput. Appl. **115**(9), 31–41 (2015). https://doi.org/10.5120/20182-2402
11. Bucci, B.A., Vipperman, J.S.: Comparison of artificial neural network structures to identify military impulse noise. J. Acoust. Soc. Am. **121**(5), 3112–3113 (2007). https://doi.org/10.1121/1.4782056
12. Goodfellow, I., Bengio, Y., Courville, A., Bengio, Y.: Deep Learning, vol. 1, pp. 326–356. MIT Press, Cambridge (2016)
13. Neural Networks and Deep Learning online book. http://neuralnetworksanddeeplearning.com/
14. Yang, Y.H., Chen, H.H.: Machine recognition of music emotion: a review. ACM Trans. Intell. Syst. Technol. (TIST) **3**(3), 40 (2012). https://doi.org/10.1145/2168752.2168754
15. Chenn-Jung, H., Yang, Y., Dian-Xiu, Y., You-Jia, C.: Frog classification using machine learning techniques. Expert Syst. Appl. **36**, 3737–3743 (2009). https://doi.org/10.1016/j.eswa.2008.02.059
16. Brian, C., Jeffrey, V.: Performance of artificial neural network classifiers to identify military impulse noise. J. Acoust. Soc. Am. **122**(3), 1602–1610 (2007). https://doi.org/10.1121/1.2756969
17. Barbarrosou, M.: Military aircraft's classification based on their sound signature. Aircraft Eng. Aerospace Technol.: Int. J. **88**(1), 66–72 (2016). https://doi.org/10.1108/AEAT-04-2014-0040
18. Authur, J.: Recognizing Sound a Deep Learning as a Case Study. Deep Learning (2016). https://medium.com/…/recognizing-sounds-a-deep-learning-case-study-1bc37444d44
19. Jeffrey, S., Mathew, A., Brian, A.: Development and implementation of metrics to identify military impulse noise. In: 149th Meeting of the Acoustical Society of America, 16–20 May 2010, Vancouver, BC Canada (2010). J. Acoust. Soc. Am. **117**, 1585
20. Cakir, E.: Multilabel sound event classification with neural networks. Master of Science thesis. Tempere University of Technology, Finland (2014)
21. Kumar, A., Raj, B.: Deep CNN framework for audio event recognition using weakly labeled web data (2017). https://doi.org/10.5281/zenodo.27878
22. Piczak, J.: ESC: dataset for environmental sound classification. In: 23rd ACM International Conference on Multimedia, Brisbane, Australia, pp. 1015–1018 (2015). https://doi.org/10.1145/2733373.2806390
23. Toghiani-Rizi, B., Windmark, M.: Musical Instrument Recognition Using Their Distinctive Characteristics in Artificial Neural Networks. arXiv preprint arXiv:1705.04971 (2017)
24. Arslan, Y.: Impulsive Sound Detection by a Novel Energy Formula and its Usage for Gunshot Recognition. arXiv preprint arXiv:1706.08759 (2017)
25. Luitel, B., Murthy, Y.S., Koolagudi, S.G.: Sound event detection in urban soundscape using two-level classification. In: Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), pp. 259–263. IEEE (2016)https://doi.org/10.1109/discover.2016.7806268
26. Lojka, M., Pleva, M., Kiktová, E., Juhár, J., Čižmár, A.: Efficient acoustic detector of gunshots and glass breaking. Multimedia Tools Appl. **75**(17), 10441–10469 (2016). https://doi.org/10.1007/s11042-015-2903-z
27. Salamon, J., Bello, J.P.: Unsupervised feature learning for urban sound classification. In: International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 171–175. IEEE (2015). https://doi.org/10.1109/icassp.2015.7177954

28. Mahana, P., Singh, G.: Comparative analysis of machine learning algorithms for audio signals classification. Int. J. Comput. Sci. Netw. Secur. (IJCSNS) **15**(6), 49–55 (2015)
29. Piczak, K.J.: Environmental sound classification with convolutional neural networks. In: 25th International Workshop on Machine Learning for Signal Processing (MLSP), pp. 1–6. IEEE (2015). https://doi.org/10.1109/mlsp.2015.7324337
30. Ptak, P., Hartikka, J., Ritola, M., Kauranne, T.: Aircraft classification based on radar cross section of long-range trajectories. IEEE Trans. Aerospace Electron. Syst. **51**(4), 3099–3106 (2015). https://doi.org/10.1109/TAES.2015.150139
31. Fernández, L.P.S., Pérez, L.A.S., Hernández, J.J.C., Ruiz, A.R.: Aircraft classification and acoustic impact estimation based on real-time take-off noise measurements. Neural Process. Lett. **38**(2), 239–259 (2013). https://doi.org/10.1007/s11063-012-9258-5
32. Øland, A.: Machine Learning and its Applications to Music. Machine Learning report. e IT University of Copenhagen (ITU) (2011)
33. Freire, I.L., Apolinario, J.A.: Gunshot detection in noisy environments. In: International Telecommunications Symposium (2010)
34. Ntalampiras, S., Potamitis, I., Fakotakis, N.: Automatic recognition of urban environmental sounds events. In: Proceedings of International Association for Pattern Recognition Workshop on Cognitive Information Processing, pp. 110–113 (2008). https://doi.org/10.1007/978-3-540-68127-4_15
35. Shelton, C.M., Vipperman, J.S., Nykaza, E.T., Valente, D.: Six noise type military sound classifiers. In: ASME 2012 Noise Control and Acoustics Division Conference at InterNoise, pp. 127–136 (2012). https://doi.org/10.1115/ncad2012-0326
36. Shelton, C.M.: Six noise type military sound classifier. Master thesis, Department of Mechanical Engineering, University of Pittsburg, USA (2013)