CONVOLUTIONAL NEURAL NETWORK MODEL USED FOR AIDING IC ANALOG/MIXED SIGNAL VERIFICATION

A. Gaita[1,2], E. David[2], A. Buzo[2], M. Grigore[2], C. Burileanu[1], H. Cucu[1], G. Pelz[2]

A significant amount of time and resources are devoted to the verification process during the development of analog integrated circuits. Although the verification process has improved over time, an excessive amount of visual inspection is still required. This verification involves a visual assessment of thousands of analog signals in order to discover various unexpected events, such as oscillations, overshoots and undershoots. This aspect of the verification process is the most time-consuming and error-prone, hence we propose a method to assist this manual verification process by employing a clustering technique that supports the visual evaluation of the signals. With the aid of machine learning algorithms such as convolutional neural networks, we have developed a method that can group waveforms by similarity, thereby identifying waveforms with odd or unexpected behavior as outliers. Through the lens of the Davies-Bouldin clustering metric and purity metric, this method provides a significant improvement over previously developed approach.

Keywords: Convolutional Neural Network, Autoencoder, K-Means, PCA, Davies-Bouldin

1. Introduction

The verification process of analog integrated circuits(IC) is a difficult operation that requires a high number of manual inspections, which take a significant amount of time. Because the level of requirements for analog ICs is increasing, it is becoming more difficult to guarantee the necessary standards of satisfaction [1] and this is due to the fact that the degree of complexity has risen. The current technique for verifying ICs requires a significant amount of human involvement in the verification process. In order to address these problems, we have developed an improved automated method for clustering the enormous amount of data that needs to be manually verified. As a result,

[1]University Politehnica of Bucharest, Romania, e-mail: gaita.andrei93@gmail.com, horiacucu@gmail.com, corneliu.burileanu@upb.ro

[2]Infineon Technologies, Neubiberg, Germany, e-mail: Andi.Buzo@infineon.com, EmilianConstantin.David@infineon.com, MihaiDaniel.Grigore@infineon.com, Georg.Pelz@infineon.com

we have increased both productivity and reliability while also accelerating the verification process as a whole.

The method presented in this article is based on convolutional neural networks (CNNs) and an auto-encoder (AE) architecture [2]. The reason for choosing this type of architecture was the fact that CNNs are responsible for removing redundancy from signals and emphasizing only the most relevant signal features [3], while the AE architecture is capable of automatically learning the main features fed by CNN layers [4]. Given these facts, the CNN-AE model approach suggested in this study achieves better results compared to the SIFT-based algorithm, regardless of the application of different metrics.

In order for this type of algorithm to be used on a broader scale, it has to be included in a tool that displays the results in an understandable manner, namely a 2D graph where each point represents a signal. To accomplish this, the Principal Component Analysis (PCA) technique was utilized to translate the feature space to the previously specified 2D space [5]. This type of representation has various advantages since the engineer can observe how diverse the signals are at a glance, or if a signal exhibits unexpected occurrences. Therefore, by employing this type of visualization we can effectively assist IC verification and integrate it into the industry as a reliable and dependable tool.

The proposed work is organized as follows: Section 2 presents previous work; Section 3 illustrates the suggested approach; and Section 4 illustrates the clustering validity of the method. Section 5 contains a description of the database of analog circuit response signals that was utilized in developing the suggested technique. In Sections 6 and 7, we provide our findings and discuss how they compare to the state of the art.

2. Previous Work

When dealing with analog/mixed signal integrated circuits, the cost of functional testing for analog transistors can be significantly higher, up to a factor of 1000, compared to testing digital transistors [6]. Hence, prioritizing the optimization of analog transistor verification is imperative for the industry.

In order to address the aforementioned challenge within the industry, there exist numerous methodologies, such as advanced sampling strategies for the Operating Condition hyperspace. These strategies are proposed in articles such as [7] and [8], where the authors presented sophisticated sampling approaches for the hyperspace which are necessary to provide greater coverage with fewer simulations. The research demonstrates that the suggested enhanced sampling methods yield comparable results to the conventional verification strategy with three times fewer runs.

Developing new verification methodologies that include a comprehensive description of how the design and verification processes should interact has been suggested as an additional approach for optimizing the verification of analog circuits. Among these techniques, we may mention an innovative methodology presented in article [9] that describes the interaction between the design, verification processes and different automated techniques. The article [10] proposes a schematic-driven physical verification, which is an automated method of functional verification.

Another way of tackling the optimization of the IC analog verification is by constructing clustering algorithms optimized for IC verification, employing Scale Invariant Feature Transform (SIFT) [11]. The approach of the SIFT-based strategy was to identify critical points of interest in time-series that contained useful information and to compute descriptors for the specific events [12]. There are two major elements that make this method unique: the incorporation of a custom keypoint descriptor and an adaptation of the SIFT methodology originally developed for use in 2D computer vision applications and now used to verify 1D signals (IC signal verification). As a result, our previous method is highly effective at extracting the primary characteristics around the events of interest, such as overshoots, undershoots and oscillations, since the concerned points are clustered around these types of events. Important aspects of this technique are data compression with Discrete Cosine Transform (DCT) and feature aggregation with a noise-reduction Bag-of-Words-type feature grouping mechanism.

3. Proposed Method

In this paper, we propose a technique for the clustering of signals measured on analog ICs. The initial stage in the clustering process is the extraction of relevant features from the measured signals. CNN were chosen so that we could extract the most representative characteristics, like patterns or shapes [13] in regard to behaviors observed in analog IC signals, characteristics capable of describing specific events such as overshoots, undershoots, or short time transients. CNN has been effectively utilized in several instances when automated feature extraction was required, such as [14] and [15]. Using multiple layers, such as convolutional, pooling and fully connected perceptron layers, we created an autoencoder architecture that can extract a limited number of coefficients capable of differentiating between these signals. The autoencoder configuration used in the proposed method can be seen in Figure 1.

These coefficients were further used in the process of clustering using K-means algorithm, where the K-means is applied to the hyperspace of the extracted coefficients of the autoencoder. The hyperspace is adapted to analog IC signals, and it is able to discriminate between signals better, but it cannot be visualized because it has more than 3 dimensions. Hence, to actually see how the clusters are distributed in this space, we need to reduce it to a dimension of 2 or 3. To achieve the goal of clustering visualization, we applied a dimensionality reduction technique called Principal Component Analysis (PCA) which linearly approximates the hyperspace to a 2D space.

For each clustering, the CNN-AE model must first go through two independent stages of training and evaluation before producing feature space. In the training phase of the model, we aim to recreate the input pictures as accurately as possible at the output using the architecture depicted in Figure 1. After the training process has updated the coefficients of the network, we will utilize the encoder presented in Figure 2 in order to retrieve relevant characteristics from the signals.

3.1. CNN-AE model

3.1.1. *Autoencoder Block.* The proposed autoencoder model seeks to automatically extract the primary characteristics of the input images by compressing the neural network coefficients into a middle layer. Autoencoders have an intermediate layer known as the "bottleneck" that is significantly smaller than the input and output layers. The bottleneck layer is a crucial element of our neural network model since it limits the information that can be transferred over the whole network, necessitating input data compression [4]. Figure 1 depicts an example of this design, where X = [X1, X2... Xn] is the input layer, Y = [Y1, Y2... Yn] is the output layer and A = [A1, A2... An] is the "bottleneck" that compresses the useful information.

3.1.2. *Convolutional Neural Network.* The use of CNN is motivated by the need to automatically extract features from the signals for many types of analog ICs and many types of tests. Moreover, this is necessary when we deal with signals that can present unexpected events, which we must represent with high accuracy. CNN is a deep learning algorithm effectively used for automatically extracting relevant features from images in articles such as [16] and [14]. CNN has the capacity to assign distinct features to certain aspects of an image, allowing them to be distinguished from one another [17]. With conventional techniques, we must manually define descriptors for certain events. This is a difficult effort to make, given that it is mostly determined experimentally as we must consider multiple types of tests and analog ICs. This algorithm has the benefit of extracting the most appropriate features to characterize IC analog electrical signals from various sources.

An alternative to CNN is represented by Feed-Forward Neural Networks [18], but CNNs are more effective at extracting relevant features. The main reason behind this is that they can effectively capture spatial relationships between various events found in a picture. The spatial relationships between events that are of interest to us are primarily event localization and event detection. It is crucial to know when a particular type of event occurs, as well as the distance between specific events. That is important because if an event occurs too soon or too late, it may indicate a functional error of the circuit. Since CNN employs convolution kernels, there are fewer coefficients propagated further in the network and this is highly advantageous because we

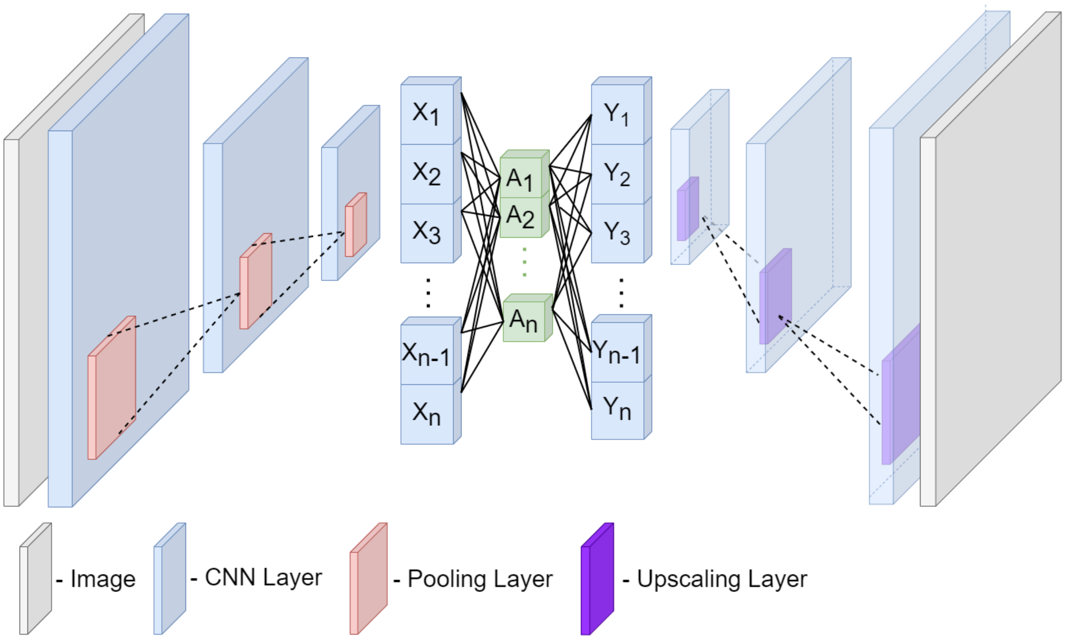

Figure 1. Autoencoder Architecture

are working with a fewer number of input coefficients for the autoencoder and a more compacted feature space.

3.2. Training of CNN-AE model

Within the autoencoder training process, we aim to update the coefficients of the neural network in such a way as to reconstruct the input at the output with the minimal possible error. By comparing the output to the input, the network is constrained to compress the information in the form of "bottleneck" layer coefficients. This compression is really useful for us because, based on these coefficients, we will construct the feature space in which the pictures will be represented.

For both the training and the testing processes, time-series signals were transformed into images to be used as CNN input. In order to verify analog signals for each test, we require a specified time interval for each set. The 1D signal is turned into a picture with a fixed time axis, so if a measurement abruptly ends, it will seem shorter in the image. Differentiating between signals that end abruptly and the other ones is a prerequisite of the analog IC testing methodology. For the training process, the initial half of the network consisted of three convolutional layers: CNN Layer 1 (filter = 16), CNN Layer 2 (filter = 8) and CNN Layer 3 (filter = 4), with a MaxPooling layer after each CNN layer, as depicted in orange, in Figure 1. In the second half of the network for image reconstruction, there are three more CNN Layers: CNN Layer 4 (filter = 4), CNN Layer 5 (filter = 8) and CNN Layer 6 (filter = 16), each of which is preceded by an Up Sampling Layer mirroring MaxPooling, which can be seen in purple, in Figure 1.

To tune the hyperparameters of the CNN-AE model presented in Table 1, we used Bayesian optimization [19]. To optimize the model, we divided the database into 70% for training and 30% for testing, in order to validate the model with the best performance and to avoid overfitting. By varying the number of hidden layer coefficients, we evaluated several setups for our specific use case. After applying the model optimization process, the following hyperparameter values from Table 1 were determined as the ones which produce the best results in the clustering process.

After the training procedure has been completed, we extracted the important features using the architecture depicted in Figure 2, where only the encoder and the PCA block are employed to reduce the dimensionality.

Table 1. CNN-AE Hyperparameters model - Bayesian optimization

Hyperparameter	**Interval**	**Step**	**Optimal Value**
CNN - kernel	[2, 7]	1	2
MaxPooling - pool size	[2, 6]	1	2
MaxPooling - strides	[2, 6]	1	2
Dropout - rate	[0.1, 1]	0.2	0.3
Activation function	[ReLu, Sigmoid]		ReLu
Bottleneck - No. of Coefficients	[64, 256]	4	128

3.3. Clustering process - K-means

In this article, we employed the K-means method in the clustering procedure in order to group the various signal types. K-means was chosen because it successfully groups linearly distinct points in a multidimensional space of characteristics. Hence, k-means detects and organizes data with important qualities. This procedure is a clustering algorithm that was used in this instance in the encoder's multidimensional feature space. To employ the k-means method, we had to specify the number of required dataset centroids called k, which are arbitrary points representing the centers of the clusters. The value k was selected based on the number of labels observable in the database.

3.4. Dimensionality reduction - PCA

A key step in the verification process is visualizing the clustering result in a simple and straightforward manner. Due to the fact that the clustering process operates in a multidimensional space, which lacks a representation of this form, this study provides an implementation of a dimensionality reduction technique. Primarily, we employed PCA, which is a very successful technique of linear transformation. It determines the size of the linear space by translating certain dimensions which contain more redundant information. Its function in this work is to reduce encoder feature space and to reduce the number of features to two, in order to plot a two-dimensional graph in which each point represents a signal. The benefit of this representation is that if one signal is significantly distinct from the others, it will be separated from the other points and it will become easier to identify.

4. Performance Metrics

It is crucial to be able to precisely monitor the efficiency of clustering performance. It is an usual procedure to empirically assess the results of the visualization, but in order to be certain that the CNN-AE method extracted useful features, we used several metrics like Purity and Davies-Bouldin. These metrics were applied to the multidimensional hyperspace.

4.1. Purity

One of the metrics used for the verification of the results is purity, which is a statistic that reflects the extent to which a group contains just one signal type. This metric is significantly more successful when dealing with a limited number of groups of signals, since it is much simpler to attain the highest level of signal purity when there are numerous and countless small clusters of signals. If we choose to correlate every point with a cluster, we will acquire a purity score of 100 percent, rendering this statistic worthless. In picking this metric, we thus considered the need to limit the number of clusters and to have balanced data because purity doesn't give useful results in the case of unbalanced data. The colloquial definition of purity is as follows:

$$P = \frac{1}{N} \sum_{m \in M} \max_{d \in D} |m \cap d| \tag{1}$$

in which M represents signals that have the same clustering label, D signals with the same label assigned following the clustering process and N is the total number of signals from group M.

4.2. Davies-Bouldin metric

The Davies-Bouldin metric is a frequent clustering performance measurement employed in the scientific literature, used to measure the effectiveness of clustering methods. This algorithm evaluates the overall quality of clustering, including how compact the points are grouped and how close the groups of points are to each other. Therefore, clusters that are more dense and more distant from the others will result in a lower score, which translates into a better performance.

It is essential to keep in mind that the ideal value for this measure is zero, which reflects optimal clustering. Hence, if the performance of the clustering

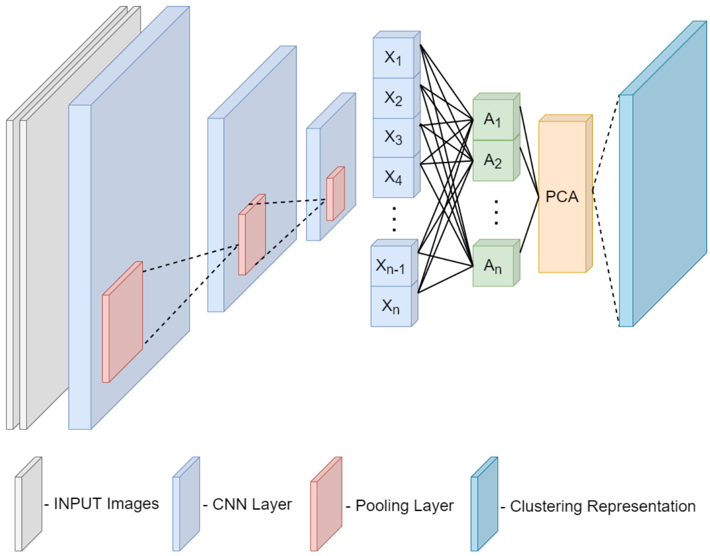

FIGURE 2. Encoder Architecture and PCA block used to generate 2D representation

method improves, the Davies-Bouldin index will reflect a lower score. This clustering performance measure may be calculated using the following formula:

$$DaviesBouldinIndex = \frac{1}{N}\sum_{i=1}^{N}\max_{j\neq i}\left(\frac{\sigma_i+\sigma_j}{d(c_i,c_j)}\right) \tag{2}$$

in which $d(c_i, c_j)$ is the distance between cluster i represented by the c_i and cluster j represented by the c_j, σ_i is the within-cluster distance average for cluster i, N is the given number of identified clusters.

5. Database

In order to prove the performance of the clustering method, we acquired a series of signals in a controlled, laboratory environment. For the purpose of the analog IC verification, the signals from the database contain behaviours illustrated by oscillations, overshoots and undershoots, as well as glitches that may occur when testing the circuit in critical conditions. For this article, we increased the database from ten sets comprising 2950 signals to twenty sets of signals exhibiting the aforementioned qualities, comprising a total of 7250 signals, where each set contained a small number of signal categories. For each distinct set of signals, a specialist manually categorized the signals into two or three classes and labeled each signal with the respective class. These labels indicate the ground truth that we'll consider while evaluating the clustering performance. Even though autoencoder training is a supervised process, clustering is unsupervised, therefore it is often recommended to compare the results with labels in order to display the overall performance. These sets of signals were also utilized to evaluate the SIFT-based waveform clustering technique in [12].

6. Results

The algorithm based on CNN-AE performs better than the method based on SIFT, as shown in Table 2. The difference in approach between both algorithms stems from the fact that the method based on SIFT takes time-series information as input, while the strategy based on CNN-AE uses picture information as input. Due to the fact that the selection of hyperparameters has a significant impact on the performance of the CNN-AE feature extraction technique, it is important to optimally select them. In circumstances where the signal length is large, the method based on CNN-AE has a shortcoming in that the image's finer details soon become buried in noise. Due to the inclusion of such signals in the database and the improved performance of the program, we can say that the method also handles this case.

Despite the fact that the purity is 100% for many of the sets, this demonstrates good separability in the multidimensional feature space, which is an achievable goal. Nevertheless, when attempting to display the data in a two-dimensional or three-dimensional environment, it is much more difficult to have clear separability. For this reason, we have implemented a second metric to determine the degree to which they are separable, as it is vital to optimize separability for a decent visualization and to facilitate the verification process. Although there are instances in which both methods have a purity of 100%, the approach delivers superior results because the clusters are more distant and compact in the feature space, resulting in a visualization improvement.

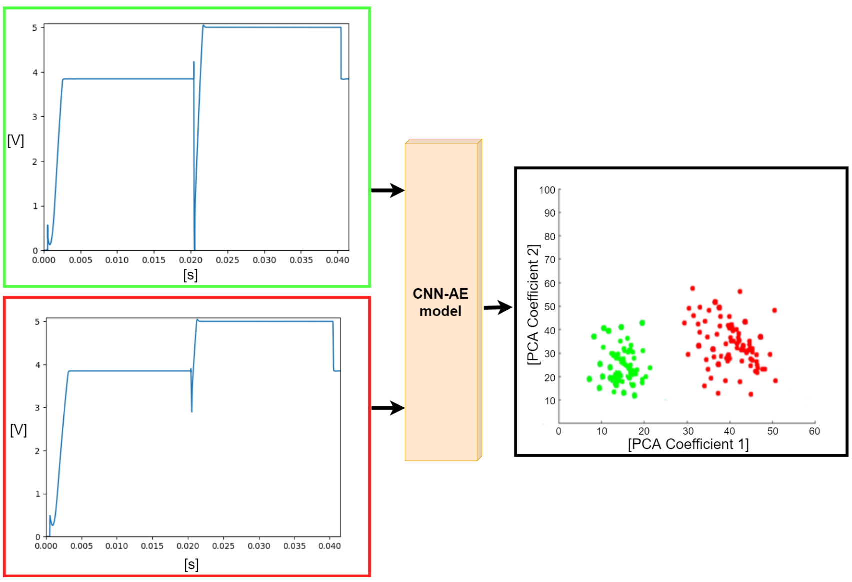

Figure 3. Example of a Clustering Representation - Set 1

TABLE 2. Comparison between SIFT and CNN-AE Results

Set Name	No. of Signals	No. of Labels	Purity (%)		Davies-Bouldin	
			SIFT	CNN-AE	SIFT	CNN-AE
Set 1	150	2	100	100	0.592	0.363
Set 2	400	4	100	100	0.370	0.229
Set 3	500	5	72.2	91	1.423	0.729
Set 4	500	6	73.6	77.6	1.488	1.198
Set 5	600	6	100	100	0.470	0.372
Set 6	600	3	100	100	0.311	0.214
Set 7	600	3	100	100	0.249	0.152
Set 8	800	3	94.3	100	0.527	0.418
Set 9	600	4	64.6	59.6	1.422	3.017
Set 10	800	3	94.8	96.8	0.663	0.558
Set 11	600	4	96.3	100	0.486	0.233
Set 12	50	3	100	100	0.336	0.185
Set 13	150	3	100	100	0.103	0.069
Set 14	150	2	87.3	100	0.881	0.365
Set 15	150	2	98.6	100	0.647	0.140
Set 16	150	3	100	100	0.335	0.277
Set 17	150	3	99.3	100	0.481	0.368
Set 18	150	3	100	100	0.164	0.082
Set 19	50	2	62	64	0.929	1.049
Set 20	100	2	74	86	0.953	0.729

In order to develop a specialized CNN-AE type model for analog verification signals, we applied Bayesian optimization. This optimization spanned all of the parameters listed in Table 1 to produce a model that was optimally suited for this type of work. After completing the optimization procedure of the results, we utilized the model hyperparameters specified in Table 1. Because the hyperparameter values were determined automatically as special adaptations of the data originating from the verification process, Table 2 demonstrates that the method yields superior results even for a much larger database in terms of both the purity metric and the Davies-Bouldin metric. As it can be seen with the purity metric, excessively large disparities cannot be highlighted because this metric does not take into account the compactness of the clusters or the distance from one another. When analyzing the data based on the Davies-Bouldin metric, we observe somewhat larger differences because, in order to calculate this score, they consider how compact the groups of points are and how far apart they are. As it can be observed with a CNN-AE neural network model with automatically modified hyperparameters, the study of both metrics yields improved results. Figure 3 is an example of the CNN-AE model's application; it shows two groups of standard signals as input to the model, along with a representation of 2D clustering in which separation between clusters is successfully achieved.

7. Conclusions

This paper presents and proves the validity of a CNN-AE strategy for optimizing the verification process. We have achieved this by combining convolutional neural networks and autoencoder networks capable of generating a feature space suitable for analog signals. By comparing the purity and Davies-Bouldin metrics proposed in this article with the previously developed SIFT-based clustering approaches [12] we demonstrated that the proposed method from this study is superior. Based on the fact that the accuracy is superior to prior findings and that the visual representation enables experts to readily inspect the result of clustering of a test, we may conclude that the proposed method has a significant and positive influence on the verification process.

REFERENCES

[1] K. Kundert and H. Chang, "Verification of Complex Analog Integrated Circuits," IEEE Custom Integrated Circuits Conference 2006, 2006, pp. 177-184, doi: 10.1109/CICC.2006.320883.

[2] X. Fang and X. Lei, "Hand pose estimation on hybrid CNN-AE model," 2017 IEEE International Conference on Information and Automation (ICIA), 2017, pp. 1018-1022, doi: 10.1109/ICInfA.2017.8079051.

[3] S. -C. Hsia and Y. -K. Yang, "Redundancy Features Detection and Removal for Simplification of Convolutional Neural Networks," 2021 3rd International Conference on Computer Communication and the Internet (ICCCI), 2021, pp. 210-213, doi: 10.1109/ICCCI51764.2021.9486779.

[4] S. Majeed, Y. Mansoor, S. Qabil, F. Majeed and B. Khan, "Comparative analysis of the denoising effect of unstructured vs. convolutional autoencoders," 2020 International Conference on Emerging Trends in Smart Technologies (ICETST), 2020, pp. 1-5, doi: 10.1109/ICETST49965.2020.9080731.

[5] S. Sehgal, H. Singh, M. Agarwal, V. Bhasker and Shantanu, "Data analysis using principal component analysis," 2014 International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom), 2014, pp. 45-48, doi: 10.1109/MedCom.2014.7005973.

[6] B. Kruseman, "Testing of Analog/Mixed Signal ICs: Past, present and future," 2015 20th IEEE European Test Symposium (ETS), Cluj-Napoca, Romania, 2015, pp. 1-1, doi: 10.1109/ETS.2015.7138759.

[7] C. Manolache et al., "Advanced Operating Conditions Search applied in Analog Circuit Verification," 2022 18th International Conference on Synthesis, Modeling, Analysis and

Simulation Methods and Applications to Circuit Design (SMACD), Villasimius, Italy, 2022, pp. 1-4, doi: 10.1109/SMACD55068.2022.9816209.

[8] C. Manolache, A. Caranica, H. Cucu, A. Buzo, C. Diaconu and G. Pelz, "Enhanced Candidate Selection Algorithm for Analog Circuit Verification," 2022 International Semiconductor Conference (CAS), Poiana Brasov, Romania, 2022, pp. 137-140, doi: 10.1109/CAS56377.2022.9934364.

[9] H. Chang and K. Kundert, "Verification of Complex Analog and RF IC Designs," in Proceedings of the IEEE, vol. 95, no. 3, pp. 622-639, March 2007, doi: 10.1109/JPROC.2006.889384.

[10] A. Arafa et al., "Schematic-driven physical verification: Fully automated solution for analog IC design," 2012 IEEE International SOC Conference, Niagara Falls, NY, USA, 2012, pp. 260-264, doi: 10.1109/SOCC.2012.6398358.

[11] Lowe, D.G. Distinctive Image Features from Scale-Invariant Keypoints. International Journal of Computer Vision 60, 91–110 (2004). https://doi.org/10.1023/B:VISI.0000029664.99615.94

[12] A. Gaita, G. Nicolae, E. C. David, A. Buzo, C. Burileanu and G. Pelz, "A SIFT-based Waveform Clustering Method for aiding analog/mixed-signal IC Verification," 2020 IEEE European Test Symposium (ETS), 2020, pp. 1-2, doi: 10.1109/ETS48528.2020.9131599.

[13] R. Chauhan, K. K. Ghanshala and R. C. Joshi, "Convolutional Neural Network (CNN) for Image Detection and Recognition," 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), Jalandhar, India, 2018, pp. 278-282, doi: 10.1109/ICSCCC.2018.8703316.

[14] S. Kido, Y. Hirano and N. Hashimoto, "Detection and classification of lung abnormalities by use of convolutional neural network (CNN) and regions with CNN features (R-CNN)," 2018 International Workshop on Advanced Image Technology (IWAIT), 2018, pp. 1-4, doi: 10.1109/IWAIT.2018.8369798.

[15] A. Ramanath, S. Muthusrinivasan, Y. Xie, S. Shekhar and B. Ramachandra, "NDVI Versus CNN Features in Deep Learning for Land Cover Clasification of Aerial Images," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, 2019, pp. 6483-6486, doi: 10.1109/IGARSS.2019.8900165.

[16] G. Chen, Y. Chen, Z. Yuan, X. Lu, X. Zhu and W. Li, "Breast Cancer Image Classification based on CNN and Bit-Plane slicing," 2019 International Conference on Medical Imaging Physics and Engineering (ICMIPE), 2019, pp. 1-4, doi: 10.1109/ICMIPE47306.2019.9098216.

[17] H. -C. Shin et al., "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning," in IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1285-1298, May 2016, doi: 10.1109/TMI.2016.2528162.

[18] B. H. K. Reddy and K. Anitha, "A Comparative Analysis for Measuring Accuracy in Recognizing Hand Gestures using Feedforward Neural Network and CNN Method," 2022 International Conference on Business Analytics for Technology and Security (ICBATS), 2022, pp. 1-8, doi: 10.1109/ICBATS54253.2022.9759008.

[19] C. W. Ahn and R. S. Ramakrishna, "On the Scalability of Real-Coded Bayesian Optimization Algorithm," in IEEE Transactions on Evolutionary Computation, vol. 12, no. 3, pp. 307-322, June 2008, doi: 10.1109/TEVC.2007.902856.