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Increasing the efficiency of deep learning performance using adaptive filters

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ABSTRACT

Deep learning algorithms have become one of the most important innovative technologies that have entered almost all areas of life. These technologies perform complex operations and deal with huge data sets. One of the benefits of deep learning is the inherent flexibility in developing approximate estimates for vast and diverse data sets. Data scientists can develop approximate estimates of almost anything using deep learning and neural networks. The main challenges in deep learning include the problem of data quality and quantity while ensuring large, diverse, and high-quality datasets. It also suffers from the problem of providing computational resources due to the high demand for powerful devices, such as processing and memory units. Additionally, it suffers from the problem of interpretability of the case due to difficulty in understanding and explaining typical decisions. This study proposes an innovative method to reduce these problems in the working mechanisms of deep learning algorithms by merging their layers and hybridizing them using adaptive digital filters. These filters help provide devices for efficient resources and memory units, in addition to the capabilities of analyzing and interpreting various states of processing unit availability. In this study, models of hybrid deep learning techniques with adaptive digital filters were designed and implemented, obtaining good results in reducing training error rates, improving the efficiency of outputs, and reducing the computational effort to high levels.

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1. INTRODUCTION

Deep learning has become a key driver of modern artificial intelligence (AI), enabling breakthroughs in image recognition, speech processing, autonomous systems, and medical diagnosis. Despite these achievements, deep neural networks often require extensive computational resources, large training datasets, and long training times. These limitations pose significant barriers for real-time and embedded applications, such as internet of things (IoT) devices, mobile platforms, and smart sensors, where power and memory resources are highly constrained. Addressing these challenges requires methods that can both accelerate training and reduce model complexity while maintaining high accuracy.

In artificial neural networks (ANNs), learning is guided by a cost function that measures the difference between predicted and actual outcomes. Reducing this cost function is central to improving model accuracy. In other words, AI learning is the cost strategy for optimizing a cycle. Thus, the limitations to making this cost function small are as follows. The main problem with the cost function representation and its enhancement is the definition of the term: the higher the cost function, the more information the ANN structure contains. Because the cost function border of adjacent needs increases, the cost function has become more complicated. Therefore, the adjacent least, or cost function, first-request subsidiary, is zero. Therefore, if AI learning is not completed at this nearby minimum, the neighborhood minimum increases the amount of information anticipated to use more boundaries while only a tiny portion of the cost function increases. AI develops the amount of available information. It gets challenging to increase the ANN structure. The cost function should be used to help complete AI learning with many local necessities. The following test is presented when the enhancement problem is addressed for different adjacent minima in a cost function [1]–[3]. Deep learning uses the substantial objective of a cost function with a few neighborhood necessities. In light of the global minimum, the cost function first-order subordinate is used in Momentum, and the researcher added the entire boundary.

Given the cost function of the first subsidiary, the Momentum technique is also an accessible strategy. The primary subordinate results from boundary learning carried out by the increased model boundaries. In any case, learning can proceed somewhat depending on the newly added cost function first subsidiary while the cost function first subordinates are zero. The most memorable subsidiary of the cost function has been included; learning continues as it progresses, and after it is finished, you will not have made the progress you could require to be able to; methods for addressing this problem include altering the learning rate and including an extra step. The Momentum technique has been given versatile properties. This is a scholarly paper based on the Momentum approach with the expansion of a versatile trait, which is a stage in the greatness of the cost function changes with its boundary. The Momentum technique fabricates a stage size given the cost function near a practical cost function with negligible worth. More specific thoughts and techniques are canvassed from top to bottom in the text. The convergence of the boundaries is characterized in this technique.

To overcome these limitations, this work proposes the integration of adaptive digital filters into deep learning architectures. By merging filtering operations with the learning layers, the model leverages the adaptive properties of infinite impulse response (IIR) and finite impulse response (FIR) filters to accelerate training, minimize error rates, and reduce computational burden. This integration allows the system to adaptively adjust weights while preserving memory efficiency, offering a promising direction for improving neural network performance in constrained environments. Figure 1 shows a schematic diagram of the adaptive deep learning technique.

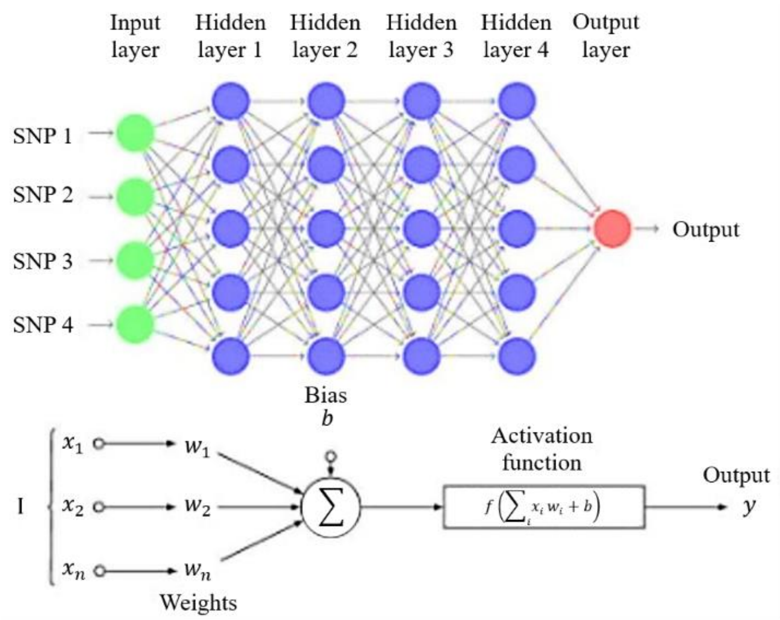

Figure 1. Schematic diagram of the adaptive deep learning technique

Several optimization algorithms, such as Momentum, root mean square propagation (RMSProp), and Adam, have been widely adopted to improve the convergence properties of deep learning. While these methods adjust learning rates adaptively and mitigate vanishing or exploding gradients, they do not directly address the structural inefficiencies of neural networks, such as redundant weights and high filter orders.

Moreover, the integration of adaptive digital filters, which are well established in signal processing for their ability to manage dynamic inputs with minimal resources, has not been sufficiently explored in deep learning frameworks. This gap motivates the investigation of hybrid architectures that combine the learning capabilities of neural networks with the efficiency of adaptive filters.

To address these limitations, this study introduces a hybrid framework that merges adaptive digital filters with deep learning models. By embedding filter operations into the network architecture, the system achieves accelerated training, reduced error rates, and lower computational burden, while maintaining model accuracy. The adaptive behavior of the filters enables efficient weight adjustment and improved utilization of memory resources, making them well-suited for environments with limited hardware capabilities. The main contributions of this paper can be summarized:

i) A novel hybrid framework is proposed that integrates adaptive IIR digital filters with deep learning models to enhance efficiency and reduce weight complexity.
ii) The proposed architecture is designed and implemented using MATLAB/Simulink, with detailed validation provided through simulation experiments.
iii) The performance of the proposed approach is compared against conventional FIR and IIR digital filters, demonstrating improvements in mean square error (MSE), efficiency, and weight reduction.
iv) The practical implications of the model are analyzed for real-world applications such as signal processing, IoT devices, and resource-limited embedded AI systems.

2. DIGITAL FILTERS IDEAS

The principal piece of any correspondence system is signal handling. Dealing with this is an unquestionable need to avoid unfortunate signs. Information can be dealt with through signal-taking care, both straightforward and digital. More unmistakable flexibility and better precision control are given by state-of-the-art signals that stand apart from essential sign management. Filters are used to cope with the sign. When it comes to handling crude indicators, digital filters are crucial. Digital signs are structures that use mathematical computations to alter a certain quality of an examined, discrete-time signal [4]. There are numerous legitimate ways to assess a digital channel's potential.

Furthermore, plans may include a variety of discerning strategies. These techniques are always used as the basis for channel detail. The simplest method for dealing with filters is to figure out how they would respond to obvious entries, such as inspiration. By combining one data set with another, the channel's response can then be inferred from other composite indicators. By combining one data set with another, the channel's response can then be inferred from other composite indicators.

In this audit, various filters, such as band-stop, band-pass, low-pass, and high-pass filters, have been used to inspect the execution of digital channels. At the channel results, the responses of various digital filters to two or three selected sound signals were observed, plotted, and played. As mentioned in the previous section, this study aims to determine whether digital filters are more effective. To accomplish this goal, the various limits of digital filters are anticipated to be optimized to a high degree. Limits, such as stage reaction, bunch delay, drive reaction, post/zero plots, size reaction, stage deferral, and step reaction, have simplified the results and identified the most common conclusion. The IIR Butterworth channel was used to get an overpowering outcome. When narrowing and stage reaction are combined, Butterworth filters are created. Because there is no stream in the pass and stop gatherings, this is occasionally recommended as a maximally level channel.

The Butterworth channel has a pretty extensive improvement fragment to reach its level from the pass band to the stop band. The Butterworth channel framework assessments are more prominent and less critical than other channel types. It is impossible to compare Butterworth filters' transient and adequacy properties [4]. Incorporating these planned redirections into actual and beneficial execution is another crucial evaluation concern. All the propagations with results for testing different cutoff points have been broken down and upheld using the filter design and analysis (FDA) device in MATLAB. A practical device for separating sound signals has been created. This section focuses on the linear time-invariant (LTI) (direct time-invariant) filters. The result of these filters is a direct progression of the entry, and their coefficients remain constant over time. Time-shifting and adaptable filters are considered in the following segments. The filter correlation between the entered and results over time can be shown using the approaching time or recurrence area approaches [5]–[10]. Using a weighted mixture of the data and prior outcome tests, the differentiation condition illustrates the effect of a discrete-time filter. For instance, the (1) may be the distinguishing condition for a first-request filter.

$$y(m) = a.y(m-1) + x(m) \tag{1}$$

In this case, the filter's result is $y(m)$ and the filter parameters of the filter-input samples are $x(m)$. The activity of impulse. It can be depicted by how the filter responds to an impulse piece of information. In samples instant at $m = 0$, for instance, the feedback that the filter from condition (1) to an impulse input is shown in (2).

$$(m) = a^m \tag{2}$$

Also, for $m = 0,1,2,3, \ldots 4$, let $y(-1) = 0$, and $y(m) = a^m = 1, a, a2, a3, a4$. The impulse reaction adds the input from each heartbeat that constitutes the sign to address the response of a direct filter to a waveform. The info beat energizes the filter at each recurrence since all its frequencies are similar. Both the impulse response and the frequency response are pairs of Fourier transforms. Each of these scenarios relates to the transfer function's zeros and poles. The ratio of the information produced by the relation to the changes z of the channel score is the exchange power of a computer channel, or $H(z)$ as in (3).

$$(Z) = \frac{Y(Z)}{X(Z)} \tag{3}$$

For example, the transfer function of a first-order digital filter is determined as in (4).

$$(Z) = \frac{a}{b-cZ^{-1}} \tag{4}$$

A valuable tool for determining a filter's behavior is its pole-zero representation. As stated in segment, the X poles and zeros serve as the fundamental bases for the denominator and numerator of the transfer function, respectively. The recurrence reaction of a filter demonstrates how it alters the sufficiency of the entered waveform's repeats with a period. One might determine a filter's repeat reaction as follows by applying the Fourier transform on the filter's impulse reaction or by essentially substituting the replacement variable ejω for the z variable z = ejω in the z-transfer function as in (5). Thus, the construction diagram of the direct-form FIR filter is presented in Figure 2 [11]–[24]. Additionally, the internal structure diagram of a time-invariant filter, which is given by (1), is shown in Figure 3 [12].

$$(e^{j\omega}) = \frac{Y(e^{j\omega})}{X(e^{j\omega})} \tag{5}$$

A polynomial ratio in the z variable could be used as a cascade format representation of the filter transfer function in relation (6).

$$H(Z) = H_1(Z)H_2(Z) \tag{6}$$

Such that every-zero transfer function of a feed-forward filter will be expressed as $H1(z)$ and could be represented as in (7).

$$H_1(Z) = \sum_{k=1}^{M} b_k Z^{-k} \tag{7}$$

Furthermore, the transfer function is $H2(z)$, which will represent the all-pole, recursive feedback filters that might be determined as in (8).

$$H_2(Z) = \frac{1}{1-\sum_{k=1}^{N} a_k Z^{-j\omega k}} \tag{8}$$

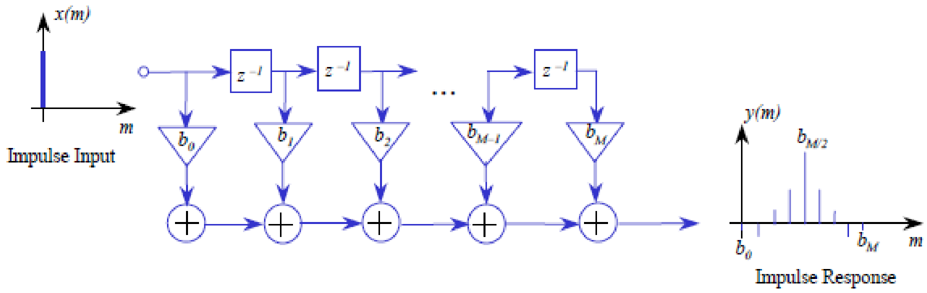

Figure 2. Construction diagram of the FIR filter

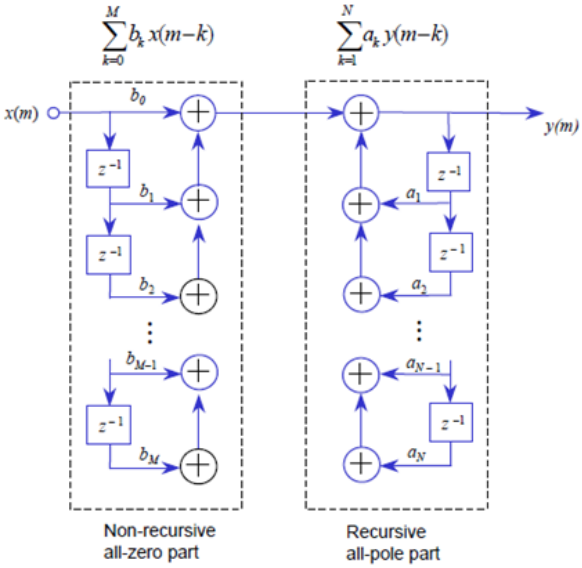

Figure 3. Construction diagram of the pole-zero IIR filter

3. DEEP LEARNING TECHNIQUES

One of the principles that concentrates on distinguishing counterfeit pictures utilizing AI was directed by scientists; they recommended a factual methodology for digital picture fraud acknowledgment by breaking down disparities in image qualities. Since then, other AI-based techniques, including deep learning schemes like recurrent neural networks (RNNs), have been developed to replicate fake images. As seen in Figure 4 [14]–[28], a feed-forward cerebrum network with at least one hidden layer and a feedback circle is a discontinuous network.

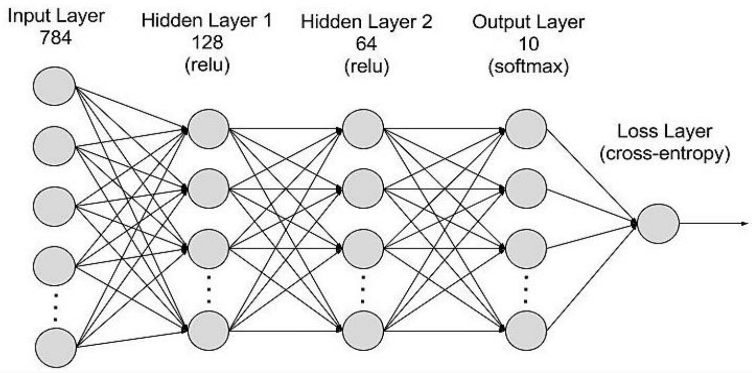

Figure 4. A feed-forward RNN network with internal layers

As displayed in Figure 4, the feedback might be autonomic, that is, the consequence of the activity of the still unknown by its technique for preparing. The feedback circuits include the utilization of postponed unit parts in a few locales, prompting a non-straight, unique way of conduct, as a brilliant framework would be supposed to have roundabout units. Different elective sorts might contrast in the technique of inward connecting. However, they accomplish a similar objective and achieve a similar outcome, which is applying reiteration. Since RNNs have internal memory, they could deal with entered sequences of variable length and show worldly elements.

Regarding the RNN algorithm's structure shown in Figure 4, one may identify the recurrent units anticipating the new timestamp as results, $x'.t$, after entering the marks window $\mathrm{Xt} - \mathrm{w}{:}\,\mathrm{t} - 1$. The network receives the entered samples, timestamp by timestamp, recursively. With the activation function set to $\tanh$ and the entered sequence $\mathrm{xt} - 1$ of the recurrent unit $\mathrm{ot} - 2$ applied, the resultant vector $\mathrm{x}'\mathrm{t}$ is calculated using (9).

$$x_t' = \sigma(W_{x'}, o_{t-1} + b_{x'}),$$
$$o_{t-1} = tanh\,(W_{o.x_{t-1}} + U_o. o_{t-2} + b_h) \quad (9)$$

Where $W_{x'}, W_o, U_o$, and b are network components are achieved with repetition when the network uses the training results to compare with the inputs to remember what it has learned along the previous steps. This means that the network learns in the long term through short-term predictions [7]–[10], [13].

4. RELATED STUDIES

Starting from the presentation of AI, ANN have been on a meteoric ascent [4]. Emerging neural structures, preparing systems, and gigantic information authorities constantly push the best in class in numerous applications in deep learning of complicated models. These are presently, to some degree, credited to quick advancements in these procedures and hardware innovation. Nonetheless, the investigation of ANN rudiments does not follow similar networks [5]. One of the most well-known ANN designs for the PC model is a lack of perception of its fundamental subtleties due to specific fascinating, unexplainable peculiarities to be noted. Tests have shown that minor information changes can influence execution, a phenomenon known as ill-disposed models [7]. It is plausible that portrayals are unidentifiable. However, convolutional networks emphatically accept that there are things. These hazards compel research on neural network activity and network upgrades, for example, improved neuron introduction, building design search, and fitting cycles. AI [8] will benefit from efforts to comprehend the properties of intelligent algorithms and develop more precise and trustworthy models. As a result, the study of ANNs is arguably the most recent area of knowledge. It also develops into legitimate multidisciplinary research that brings together experts, software engineers, biologists, mathematicians, and physicists. Some of the odd behaviors of ANNs were consistent with noisy frames, which were generally very sensitive, nonlinear, and hard to predict. Analyzing the many networks connected by the neural network, the confounding cycles, and their connections to the other networks, such as the various networks, is the fundamental design of complex networks (CN). For example, the neural network of the *Caenorhabditis elegans* worm has been demonstrated to exhibit the little world C.N. phenomena [7]. The average reticular improvement of the cerebrum stem [20], cortical association examinations [19], and encephalography accounts [8] are examples of comparative topological qualities observed in human mind networks.

Numerous approaches have been used to work on the initial gradient plummet calculation. Models include “versatile gradient” tactics like Adam and RMSProp [11], [13], which combine RMSProp [23] with adaptive gradient (AdaGrad) [24] and add a “Momentum” element to the update rule. These methods have been frequently used in deep neural networks. In recent years, much research has been conducted into novel methods for modifying the learning rate. Non-monotonic learning rates and support for the potential for repeating learning rates are essential to such endeavors. A method is presented that provides a Momentum learning rate. According to an ongoing speculative study, stochastic gradient plummet is sufficient to optimize over-defined neural networks while making negligible assumptions. It is intended to methodically determine the optimal learning rate, rejecting the notion that the primary small learning rates should be applied, and then provisionally demonstrate validity of claims. Determining the step size in gradient-based advancement based on the unfortunate gradient that illustrates how each obscure barrier approaches convergence is essential. Versatile rate scheduling has been developed to achieve this goal and ensure that the method converges quickly after training, considering boundaries such as RMSprop, Adam, and AdaGrad [12].

4.1. Contributions of the study

This study advances the field of deep learning by introducing a hybrid framework that integrates adaptive IIR digital filters into neural network architectures, providing both theoretical, and practical improvements over existing methods. Unlike conventional optimization strategies such as Momentum, RMSProp, and Adam, which primarily accelerate convergence without addressing structural inefficiencies, the proposed approach reduces network complexity by minimizing the number of weights while maintaining accuracy. The central theme of this work is the enhancement of training efficiency through the dual function of adaptive filters as preprocessing units and dynamic weight-adjustment mechanisms. The design specifically aims to lower error rates, improve computational efficiency, and achieve significant weight reduction, making the model highly suitable for real-time and resource-limited applications. Comparative evaluations against standard FIR and IIR filters confirm the superiority of the proposed system in terms of MSE, efficiency, and weight optimization, thereby establishing its contribution as both novel and impactful within the domain of intelligent signal processing and embedded AI.

5. METHOD

The methodology consists of three main stages: i) design of adaptive IIR digital filter, ii) integration of filter with the deep learning model, and iii) performance evaluation through MATLAB/Simulink simulations. The adaptive filter serves as both a preprocessing and a weight-adjustment mechanism, while the neural network executes the learning task. The combined framework is tested using different design parameters, and results are validated through comparison with conventional FIR and IIR filter approaches.

In this section, the proposed deep-learning neural network is designed and modified with the help of an adaptive IIR digital filter. The objective is to exploit the filter's capabilities to accelerate training and dynamically update the weights of the neural network. The memory units in the filter also support analysis and storage operations that are typically absent in deep learning algorithms, thereby improving training efficiency and reducing error rates.

The adaptive IIR filter was developed using MATLAB 2020b digital filter design tools. A 10th-order low-pass filter structure was selected, with coefficients adaptively updated during training based on the MSE criterion. This iterative optimization minimized the error between target and predicted outputs. Compared with FIR filters, the IIR structure provides lower computational complexity and requires fewer coefficients to achieve similar performance, making it suitable for real-time applications. The proposed framework was implemented and tested in MATLAB/Simulink, with the design reviewed against established specifications. A compensator mechanism was included to calculate differences between the IIR filter coefficients and the neural network responses, enabling dynamic adjustment during training. This variable approach reduced delays and computational overhead while enhancing the integration of filtering and learning processes. Figure 5 presents a block diagram of the proposed deep learning adaptive IIR model. Also, Figure 6 displays the details of the software simulation of the deep learning adaptive digital filter model.

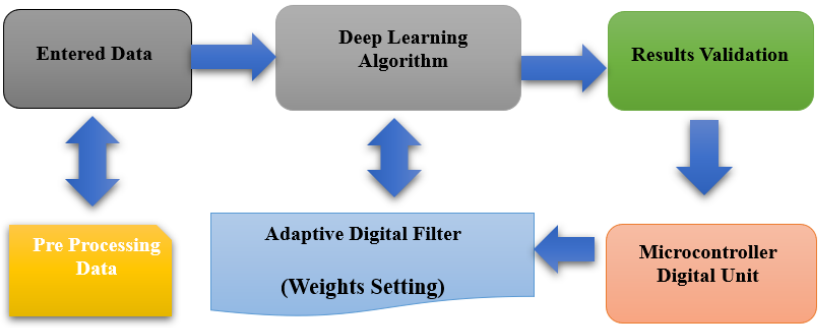

Figure 5. Block diagram of the proposed deep learning adaptive digital filter model

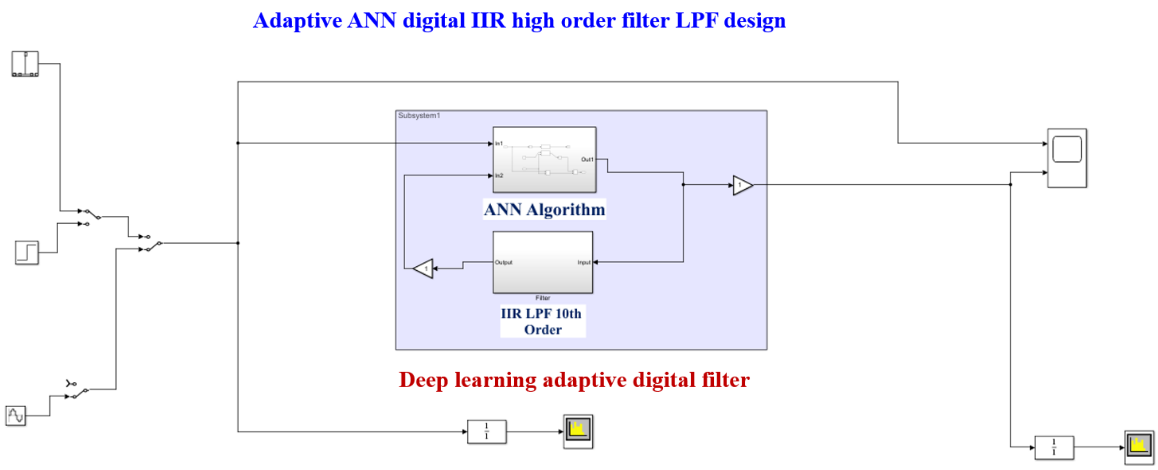

Figure 6. The details of the software simulation of the proposed deep learning adaptive digital filter model

The internal construction of the suggested model has been further explained and illustrated in Figure 7. Figure 7(a) shows the digital IIR structure, and Figure 7(b) shows the deep learning neural network construction. By viewing the details of the system designed in Figure 6, it is possible to notice the details of the software simulation of the deep learning algorithm model adapted to the digital filter. The data entered into the model is filtered, starting with the digital filter weights, and then the results are sent to the neural network algorithm so that training is completed through the hidden internal network layers and the neurons.

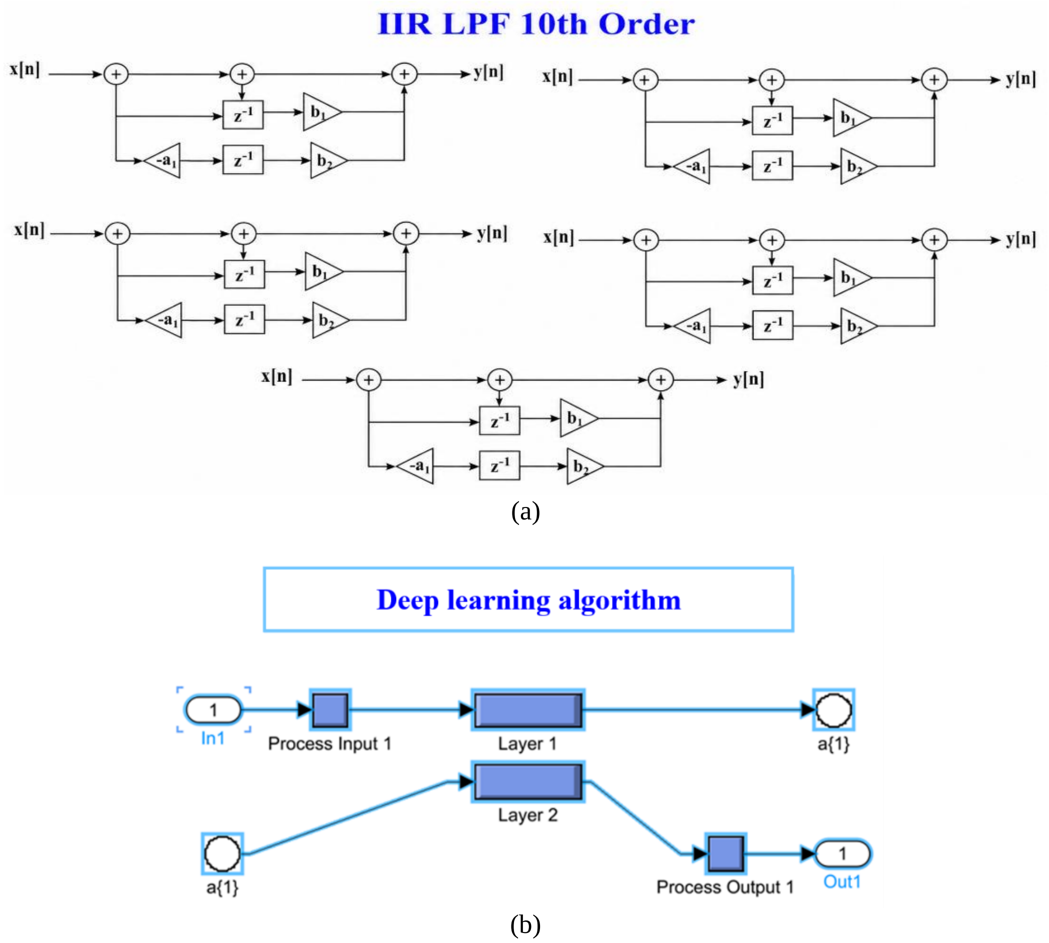

Figure 7. The internal construction of the suggested model of (a) digital IIR structure and (b) deep learning neural network construction

The deep learning model was implemented as a feed-forward ANN consisting of an input layer, one hidden layer with 10 neurons, and an output layer. The hidden layer employed a tanh activation function, while the output layer used a linear activation. Training was carried out using backpropagation with a learning rate of 0.01, and optimization was guided by the adaptive filter coefficients. The filter acted as an auxiliary unit to update network weights dynamically, reducing convergence time. The integration ensured that signal preprocessing, weight adjustment, and error correction were performed in a single framework. The adaptive digital filter design was performed using MATLAB's digital filter design application. This application provides all the software tools necessary to create a digital filter model on any basis using various and efficient windowing techniques. Figure 8 presents the graphical user interface of the digital filter design tool.

The design parameters and specifications of the adaptive digital filter are adjusted according to the details shown in Figure 8. The required digital filter is created and designed, and its spectral and phase responses are tested. Figure 9 shows the preliminary design results. Moreover, the proposed neural network design structure's design architecture is illustrated in Figure 10. Referring to Figure 10, the number of neurons (weights) is controlled such that the weights required for recognizing the input data samples are normalized to obtain the target data samples. In this design, the proposed model was modified by using

10 neurons as learning weights to build the hidden layer in addition to the input and output layers, enhanced with activation functions.

Next, the flow chart of the proposed deep learning adaptive digital filter model has been demonstrated in Figure 11. All simulations were conducted in MATLAB/Simulink 2020b on a system with an Intel Core i7 processor, 16 GB RAM, and a Windows 10 environment. Input signals included sinusoidal and random test signals sampled at 44.1 kHz. Filter parameters such as cutoff frequency (10 kHz) and filter order (7) were selected based on design specifications. The performance of the proposed hybrid model was evaluated in terms of MSE, convergence rate, weight reduction, and efficiency (η). The results were benchmarked against conventional FIR and IIR filters under the same simulation conditions.

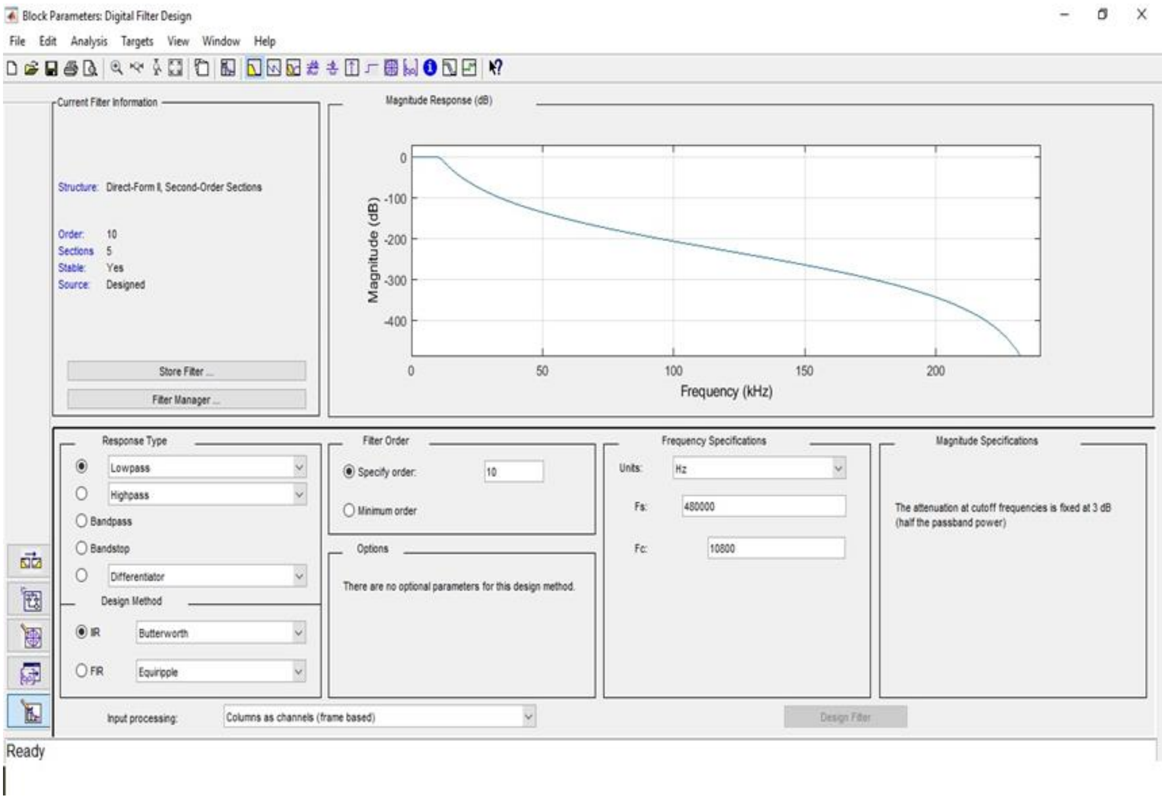

Figure 8. The graphical user interface of the digital filter design tool

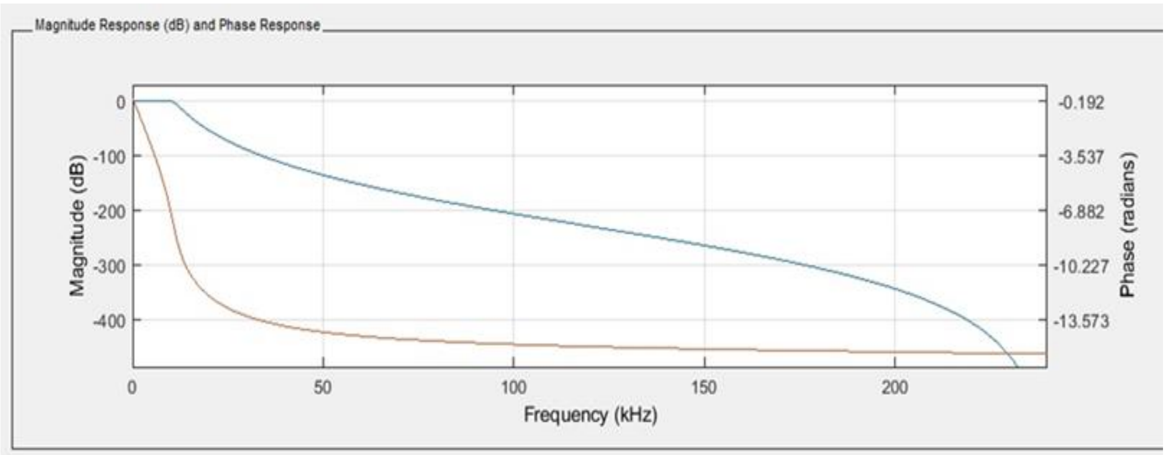

Figure 9. The designed amplitude and phase responses of the digital IIR low-pass filter (LPF) 10th-order filter nominated for the proposed model

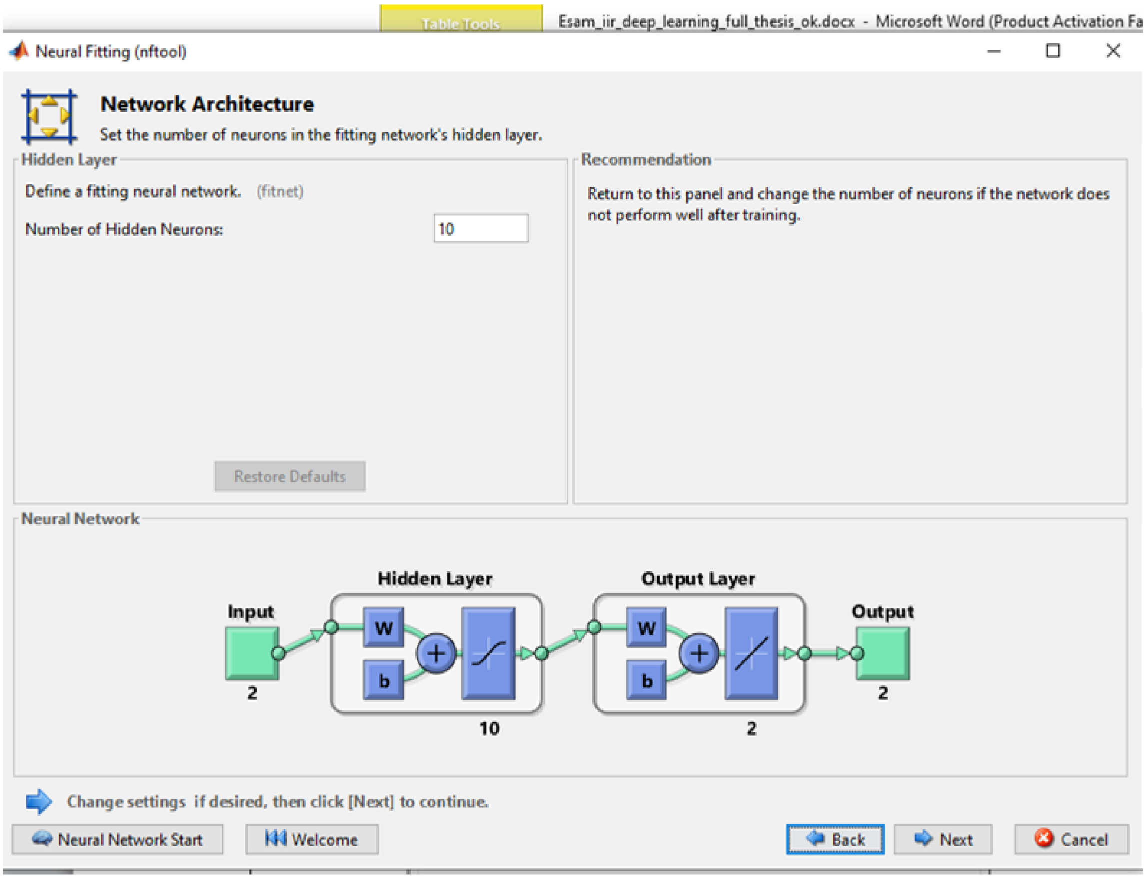

Figure 10. The ANN algorithm architecture tool employed to construct the network’s layers

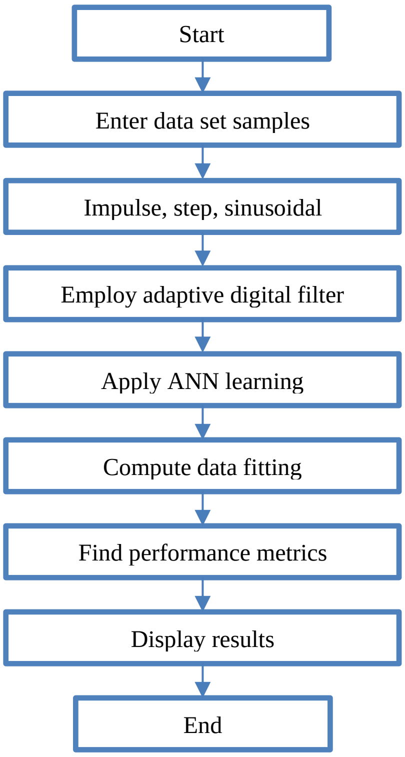

Figure 11. Flow chart of the proposed deep learning adaptive digital filter model

6. RESULTS AND DISCUSSION

The proposed models have been implemented and examined successfully under the specified design constraints. The achieved results have been illustrated in the incoming figures. Figure 12 demonstrates the sinusoidal responses for the proposed 10th-order adaptive digital IIR-LPF implementation against the deep learning algorithm model. Also, the impulse response of the proposed model has been achieved, as presented in Figure 13. Moreover, the frequency responses of the entered and resulting samples are introduced in Figures 14 and 15, respectively.

Figures 14 and 15 show that the frequency response of the results of implementing the proposed model shows a high convergence to the response of ordinary high-exponential digital filters. That is, the result of hybridizing the deep learning algorithm with a low-exponential digital filter is equivalent to the work of high-exponential digital filters. Furthermore, the updated neural network weights have been achieved and illustrated in Figure 16. Also, Figure 17 shows the impulse response (weights) for high-order digital filters. The difference between the proposed model and the digital high-order LPF is clear in shortening the number of weights, thus reducing the compositional complexity and cost of updated neural network weights.

By looking at the achieved results from this research, one might notice the improvement in the response of the adaptive digital filter in the response of the deep learning algorithm. The frequency response of the results of implementing the proposed model showed high convergence compared to the response of ordinary digital filters with a high exponent. That is, the result of hybridizing a deep learning algorithm with a low-exponential digital filter is equivalent to the work of high-exponential digital filters. Table 1 compares the results of the proposed adaptive neural network model with the regular digital filter.

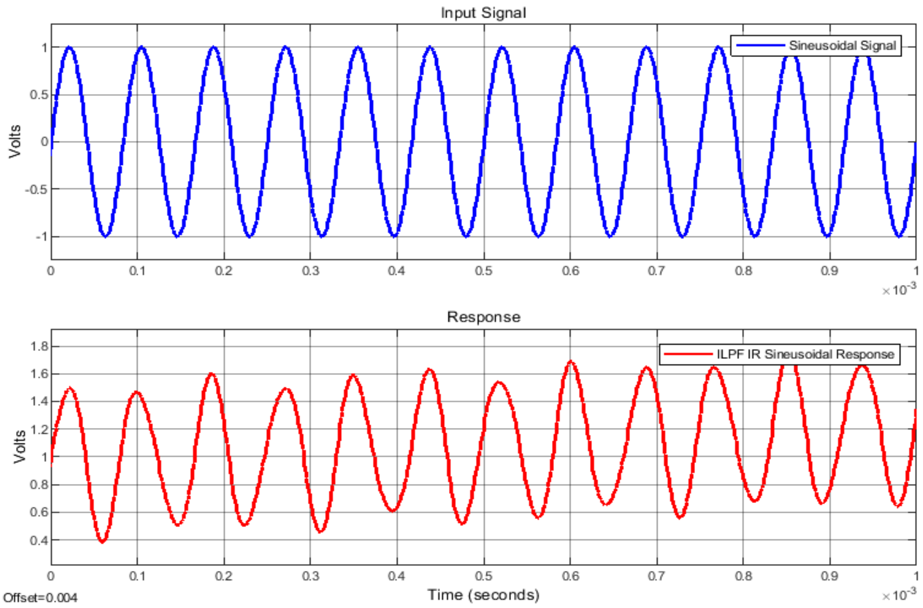

Figure 12. Sinusoidal response for the simulated proposed 10th-order IIR-LPF deep learning model

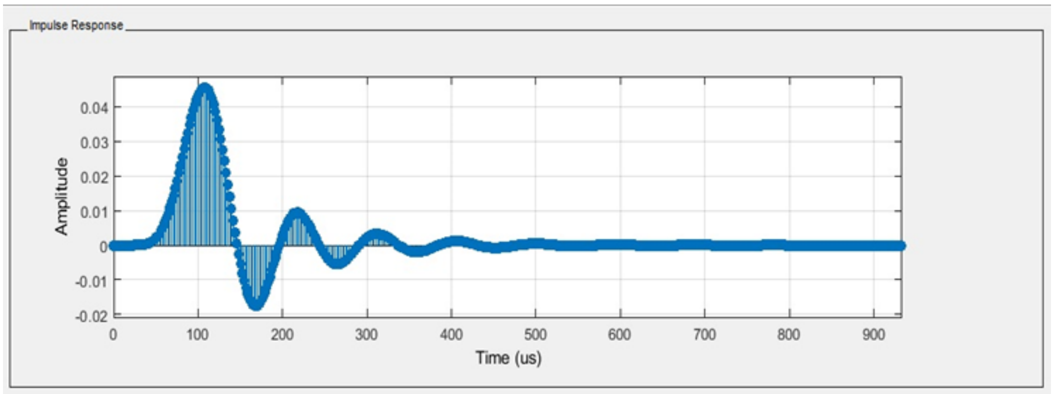

Figure 13. Impulse response of the proposed model

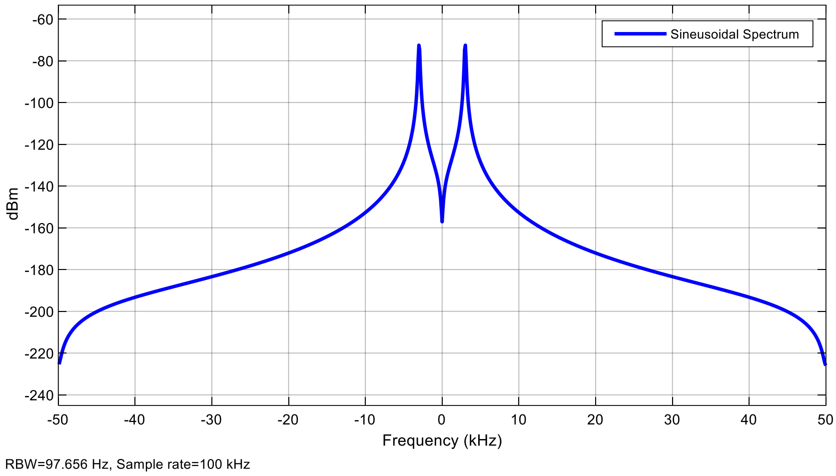

Figure 14. The entered samples frequency response for the proposed 10th-order ANN digital LPF

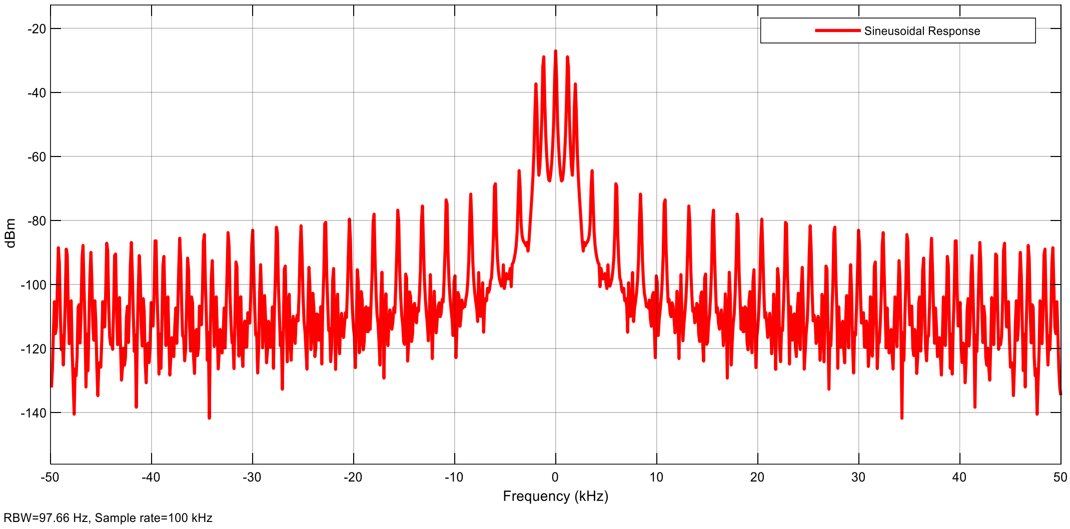

Figure 15. The resulting sample frequency response for the proposed 10th-order ANN digital LPF

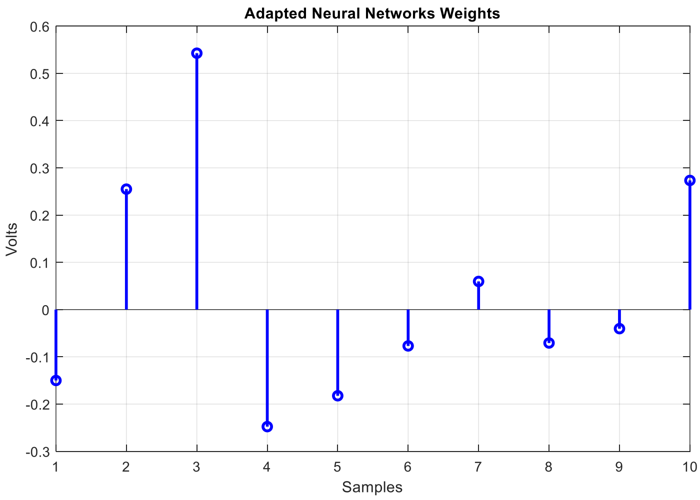

Figure 16. The obtained updated neural network weights

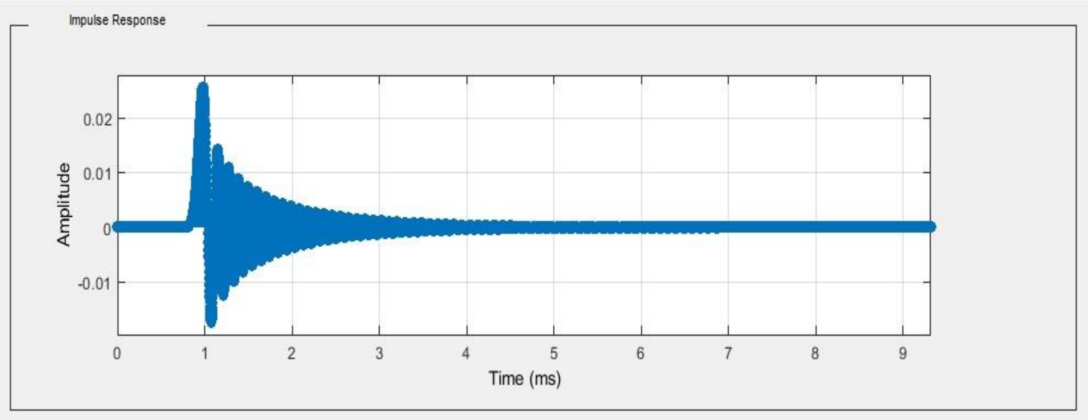

Figure 17. The impulse response (weights) for high-order digital filters

Table 1. Comparison between the results of the proposed adaptive neural network model and the regular digital filter

Model	Digital filter order	Weights number (impulse response) samples	Cutoff frequency (Hz)	Efficiency (η) (%)	Error rate MSE (%)	Weight reduction ratio (%)
FIR LPF	100	100	5-10	96	0.4	-
IIR LPF	100	100	3-10	96.5	0.35	-
Proposed	10	10	1-20	98	0.12	90

7. CONCLUSION

This study presents a proposed method to reduce the problems of working mechanisms in deep learning algorithms by merging and hybridizing their layers using adaptive digital filters. Interpolating these filters helped provide devices with efficient resources and memory units, in addition to analyzing and interpreting the various states of processing unit availability while reducing weights. In this study, models for hybrid deep learning techniques with adaptive digital filters were designed and implemented, and good results were obtained in reducing training error rates to 0.12%, improving the output efficiency to 98%, and reducing computational effort by 90%. Despite these encouraging outcomes, the study has certain limitations. The experiments were conducted in a simulated environment using limited test signals, which may not fully capture the complexity of large-scale or real-time datasets. The proposed framework was implemented using a relatively simple neural architecture; extending the approach to deeper or more CN could reveal additional challenges. Future research may explore the integration of adaptive filtering with advanced deep learning models, such as convolutional or RNNs, the application of this framework to real-world datasets in speech or image processing, and hardware-level implementation for embedded and IoT devices. These directions would help validate the scalability and robustness of the proposed approach and provide a pathway for further practical adoption.

8. PRACTICAL IMPLICATIONS

The findings of this study have significant practical implications for the deployment of deep learning in real-world applications where efficiency, speed, and resource optimization are critical. By integrating adaptive IIR digital filters into neural network architectures, the proposed framework reduces the number of weights, accelerates training, and lowers error rates without requiring extensive computational resources. This makes the approach particularly valuable for embedded systems, IoT devices, and portable platforms, where hardware and energy constraints limit the use of conventional deep models. In addition, the ability of the framework to achieve comparable or superior performance with fewer parameters offers benefits for large-scale signal processing tasks, such as speech and image recognition, real-time monitoring, and medical diagnostics. The results suggest that the method can support the development of lightweight and scalable AI solutions that are better aligned with industrial, healthcare, and consumer technology demands.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY

No datasets were generated or analyzed during the current study.

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