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REGULAR ARTICLE

Enhancing the Implementation and Reliability of Nanomaterial Detectors through Deep Learning Optimization

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Improving the reliability and implementation are critical in real-world applications, and the inherent unpredictability of non-materials renders it complicated to integrate Nanomaterial (NMs) detectors into these environments. Reliable presumptions can be constructed based on the data produced by such sensors using Deep Learning (DL), which is a potent method. In this study, we proposed a novel method called Fine-Tuned Genetic Algorithm Based Dynamic Deep Neural Network (FTGA-DDNN) which is computationally costly to train, yet it yields the most efficient result when evaluated the internet, maintaining a reasonable level of reliability. This can be beneficial in dynamically changing environments where the algorithm needs to explore new possibilities while exploiting known solutions. Through DL optimization, the goal of improving the implementation and dependability of nano-material detectors is to increase their adaptability and efficacy in a variety of situations. We present a comparative analysis of the results obtained from our proposed technique against other existing methods. Our findings indicate superior performance in average error, average absolute error, and semi-log testing time, showcasing the efficacy of the FTGA-DDNN approach. In summary, this allows us to forecast and predict the filter function later on, improving the DL algorithms' accuracy and the filters' usefulness over extended periods.

Keywords: Deep Learning (DL), Nanomaterials (NMs), Nanotechnology, Fine-tuned genetic algorithm-based dynamic deep neural network (FTGA-DDNN).

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1. INTRODUCTION

Nanotechnology is the aggregate term for all modern innovations that apply or function dimensionally at nanoscale levels. Managing and designing technological findings arising from the formation of novel features at the nanoscale (one billionth of a meter) is known as nanotechnology. A material's size at the nanoscale ranges from 1 to 100 nm. A nanoparticle (NPs) is a three-dimensional, tiny substance or material. One component of a composite structure made of several materials or substances at the nanoscale is called a nanocomposite [1]. Nanotechnology is at the intersection of technological innovation across a wide range of technical areas and environmental areas. The global market for nanomaterials is expected to reach a value of over $90.5 billion by the end of 2022, and demands for both consumers and commercial items with nano-enhanced features have been rising recently [2]. The flexibility of nanomaterials can lead to the development of distributable, flexible, and portable electronics, electric cars, grid-scale storage, and interaction with biological systems and living environments. To prevent these deficiencies, nanoparticles with different capabilities should be incorporated into innovative structures on the nano- and microscales [3].

The essential fundamentals for elastic and adaptable technologies that can satisfy these high requirements are nanomaterials. It has been demonstrated that nanomaterials exhibit superior material properties compared to their large equivalents. Systems and devices with nanoscale characteristics can be created using both top-down and bottom-up methods [4]. The work is mainly focused on using nanotechnology to utilize computer device reductions and large storage capacity as it

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presents a potential connection between nanotechnology and the macroscopic environment [5]. High-performance position sensing is an important basis for demanding applications such as molecular- and mechanobiological experimental physics, monitoring single electron spins and trapped ions, nanomechanical transduction and sensing, and cutting-edge atomic force microscopy. Modern metrics rely heavily on position-sensitive detectors (PSDs), which are sensors that identify the location of a light spot [6]. Nanotechnology's progress in biosensors, particularly electrochemical biosensors, is gaining prominence in the diagnostics industry due to its ability to conduct electricity, chemical resistance, and large surface area. [7]. Nanotechnology offers possibilities to create superior substances with enhanced characteristics for use in a range of possible application areas. The characteristics of a material undergo significant changes when its dimensions are reduced from macro-size to micro-size (nano-size) since the atoms within nanoparticles are perfectly organized [8]. The study aims to improve the reliability of nanomaterial detectors by optimizing FTGA-DDNN for adaptability and effectiveness across various scenarios.

2. RELATED WORK

The study [9] provided an overview of the existing concepts for particle detection and characterization, which serve as the foundation for some of the recently developed methods. Effective evaluation of the outcomes of the utilized analysis requires the application of the measurement concept. The study [10] described the nanoparticles-based biosensors have become more popular because of their great applicability across almost all technological and biological domains. As nanotechnology has grown, it has led to the development of nanowires (NWs), nanorods (NRs), carbon nanotubes (CNTs), quantum dots (QDs), dendrimers, and noble metal and metal oxide nanoparticles. It has also resulted in contemporary breakthroughs in biosensor technologies.

The study [11] examined the application of nanoparticles in the building sector as evidence of their benefits, as well as the short- and long-term impacts of this sector's nanoscale on humans and the environment. To enable the findings to be broadly applied, the advantages of using nanoparticles in common materials. The study [12] explained the distinct capacity of optical nanomaterials to regulate the propagation of electromagnetic (EM) waves has led to a significant increase in the field of nanophotonic. The Study [13] described the modern electrochemical detectors and sensor technology based on nanomaterial for six primary classifications of pharmacological substances antidepressant, antiviral, anti-inflammatory, antimicrobial, and anticancer are identified and measured. The study [14] described Particle identification, counting, and measurement are crucial steps in a lot of research projects. In the report on the automatic identification of metal nanoparticles placed on highly aligned pyrolytic graphene using deep learning applied to images captured by scanning tunneling microscopy (STM). The study [15] explained the improvement consists of three recurrent and two convolutional architectures to provide a fair and impartial assessment of their effectiveness. In addition, the ways evolutionary optimization of such systems is affected by selecting F1 scores and accuracy as the performance measure. The paper [16] provided the most recent developments in the field of carbon-based nanomaterials used as electrode-equipped sensor technology are explained. The possibilities and prospects of this industry have been discussed, focusing in particular on how these nanomaterials have recently been used as biosensors with electrodes for detecting a variety of biomolecules.

3. METHOD AND MATERIALS

Data collection

The transmittance values were acquired throughout a wide spectrum ($351\ \text{nm} < \lambda < 1100\ \text{nm}$), and the wavelength-dependent measurements were repeated 110 times to determine the identities of each of the 11 nanomaterial filtration. As indicated before, repeated data collection was performed to take into consideration the variations, oscillations, and drifting that frequently occur during actual metrics, especially in systems that are based on nanomaterials, which are typically sensitive to their environment. A total of seventy-five thousand training samples ($M = 750 \times 100$) were obtained by labeling one hundred of the 110 spectra of each nanomaterials filter as sample-label pairs or training data. Essentially, the test samples were ignored in the training phase and were only visible to the machine-learning models during the testing phase [17].

Fine-tuned genetic algorithm-based dynamic deep neural network (FTGA-DDNN)

The FTGA-DDNN approach, the activation mechanism, the ideal variety of secret layers, and the number of neurons in each hidden layer are all determined to build the Dynamic Deep Neural Networks (DDNN) model architecture. DDNN models usually consist of three primary layers: an output layer, a few hidden layers, and an input layer. The number of hidden layers determines the architecture's depth. GA-based methods are frequently used to train DDNN, and it can be difficult to analyze the dynamics of such training. Initially, it often requires an extensive amount of parameters due to their extremely nonlinear nature, and the DDNN model's diagram is also shown in Fig. 1.

This population-based algorithm, developed through that evolutionary process, presents the concepts of evolution and the survival of the most suitable. It initiates a collection of responses, called genetic material, and facilitates their growth and development. This process can be repeated until the optimal possible

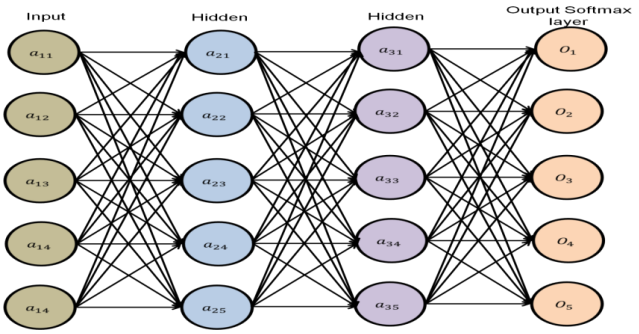

Fig. 1 – Architecture of DDNN Model

outcome is obtained. Initially, FTGA implementation maintains each individual as a parameter vector θ. However, with massive populations and enormous deeper and broader neural networks, this technique scales substandard in memory and network transmission costs to maintain the nanomaterial detector. The encoding of each parameter vector as a series of randomized samples allows for the efficient storage of enormous variable vectors that yield the nanomaterial detector series of mutations that created each θ, from which each θ can be rebuilt, together with an initialization seed. Fig. 2 shows a sequential construction of a synthetic algorithm.

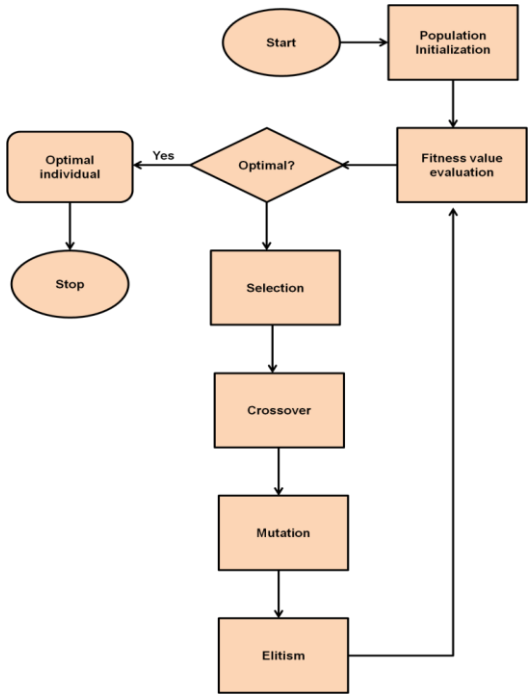

Fig. 2 – Structure of the FTGA

The following are the primary FTGA stages:

Stage 1

Initialization: The initially generated individuals are created by the user or at randomized points in the region of search. The potential solution set O makes up the initial population. In general, the initial collection of the population is created randomly.

$$O = \{O_1, O_2, \dots, O_{pop\_size}\} \quad (1)$$

$$O_j = [O_{j1} O_{j2} \ \dots \ O_{ji} \ \dots . O_{jno\_value}] \quad (2)$$

$$j = 1,2, \dots, pop\_size; \quad i = 1,2, \dots, no\_vars \quad (3)$$

$$para^i_{min} \ \leq \ Oj_i para^j_{max} \quad (4)$$

where pop_size indicates the magnitude of the populations; no_vars indicates the amount of factors that need to be adjusted $o_{ij}, j = 1,2, \dots, pop\_size; i = 1,2, \dots, no\_vars$ are the parameters to be tuned, $para^j_{max}$ and $para^i_{min}$ are the lowest and greatest values of the variable, o_{ij} respectively for all j. Eq. (1) through (4) demonstrate that certain so$_{ij}$ candidate solutions are present in the possible solution set O.

Stage 2

Evaluation: The fitness values of the potential options are assessed following the initialization of the general population. A predetermined fitness function can evaluate every chromosome in the population. In this procedure, the more efficient chromosomes produce higher values. Eq. (5) illustrates that the fitness coefficient used to evaluate a genome in the population can be expressed. Depending on the requirement, the fitness function might take several forms.

$$fitness = e(O_j) \quad (5)$$

Stage 3

Selection: After analysis, the chromosomes that are considered the best are inclined to be selected for the next generation. To determine the fitness probability, we need to calculate the fitness of each one. Through the process of spinning the roulette wheel, two chromosomes will be chosen from the population to undergo genetic treatments for reproduction. High-potential parents are thought to have superior infants. One way to make a decision is to give it an edge r_j to the chromosome O_j which is represented in Eqs. (6) and (7).

$$r_j = \frac{e(O_j)}{\sum_{l=1}^{pop\_size} e(O_1)}, j = 1,2, \dots, pop\_size \quad (6)$$

$$\hat{r}_j = \sum_{l=1}^{j} r_l \ \ j = 1,2, \dots . , pop\_size \quad (7)$$

To begin the decision-making procedure, a nonzero floating-point number is generated at randomly $c \in [0,1]$, and the selection procedure demonstrates that chromosomes with a greater $e(O_j)$ have a greater likelihood of being chosen. The most effective genes should therefore reproduce more, the average remains identical, and the most harmful ones eventually grow obsolete. Only two chromosomes have to be chosen throughout the selection step to conduct the genetic procedures.

Stage 4

After the phase of selection, the genetic operations are

to produce certain additional genomes from the offspring's parents. The transformation and crossover operations are among them. Crossover: The crossovers are a consequence of combining two or more parental solutions to create distinctive perhaps improved options. The crossover procedure is primarily used to exchange chromosomes and information acquired during the selection process between the two parents. The pair of parent's o_1 and o_2 will produce one offspring. First, the following processes are to be utilized to produce four chromosomes are shown in the following Eqs. (8) to (12).

$$PT_d^2 = \left[PT_1^2 PT_2^2 \dots PT_{no_{vars}}^2\right] = O_{max}(1-\omega) + \max(O_1, O_2)\,\omega \quad (8)$$

$$PT_d^3 = \left[PT_1^3 PT_2^3 \dots PT_{no_{vars}}^3\right] = O_{min}(1-\omega) + \min(O_1, O_2)\,\omega \quad (9)$$

$$PT_d^4 = \left[PT_1^4 OS_2^4 \dots PT_{no_{vars}}^4\right] = \frac{(O_{max}+O_{min})(1-\omega)+(O_1,O_2)\omega}{2} \quad (10)$$

$$O_{max} = \left[para_{max}^1 para_{max}^2 \dots para_{max}^{no\_vars}\right] \quad (11)$$

$$O_{min} = \left[para_{min}^1 para_{min}^2 \dots para_{min}^{no\_vars}\right] \quad (12)$$

Mutation: Once two or more parental chromosomes have crossed across, a mutation randomly modifies the solution. Numerous techniques for modifications take place, and a different value is randomly inserted in the place of the generations throughout the mutation process. The purpose of the mutation procedure is to alter the chromosomal genes. As a consequence, chromosomal traits inherited from their parents can be modified. The mutation operation produces three additional progeny are shown in the Eq. (13).

$$nos_j = \left[PT_1 PT_2 \dots PT_{no_{vars}}\right] + \left[a_1 \Delta nos_1\ 2\Delta nos_2 \dots a_{no_{vars}} \Delta nos_{no_{vars}}\right] \quad (13)$$

A mutation procedure can be performed using a variety of techniques, such as boundary mutation, uniform mutation, and non-uniform mutation. A randomly chosen gene's value can be changed by a boundary mutation to its upper or lower bound.

4. RESULT AND DISCUSSION

The comparison with several prominent approaches like K-Nearest Neighbors (KNN) [18], and Bayesian [18] was examined in this section. To ascertain whether the FTGA-DDNN suggested method is more successful than another method previously utilized.

4.1 Estimation of Average Error

The wavelength samples that were gathered have a resolution of 1 nm. Errors are often estimated to evaluate the reliability of estimates, designs, or measurements in a variety of domains, most notably statistics, machine learning, and scientific measurements. The outcomes demonstrate that various techniques differ in wavelength estimation accuracy. Fig. 3 depicts the FTGA-DDNN wavelength using an identical training data set that includes the samples. Initially establish the estimation error percent and consider how effective our wavelength estimators are shown in Eq. (14).

$$error\% = \frac{\left|\lambda_{Groundtruth(nm)} - \lambda_{Estimated(nm)}\right|}{\lambda_{Groundtruth(nm)}} \times 100 \quad (14)$$

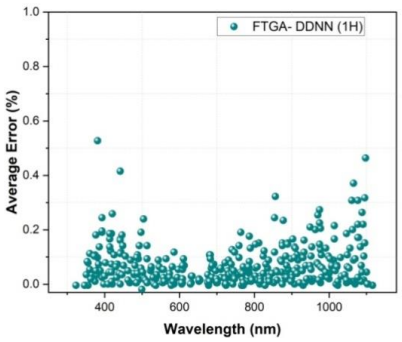

Fig. 3 – Structure of wavelength towards average error

4.2 Comparison of Average Absolute Error

The degree to which observations or estimates parallel actual or anticipated values can be summarized using the average error. The average absolute error values for each deep learning model under various training data circumstances are shown in the following Table 1 and Fig. 4. Nanomaterial is utilized as the error's unit of measurement.

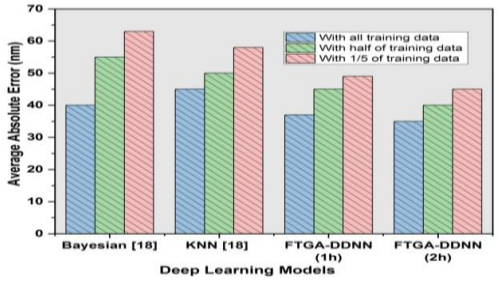

Fig. 4 – Comparison of Average Absolute Error

Table 1 – Evaluation of Average Absolute Error

Deep Learning Models	**Average Absolute Error (NM)**		
	With all training data	With half of the training data	With 1/5 of training data
Bayesian [18]	40	55	63
KNN [18]	45	50	58
FTGA-DDNN (1h)	37	45	49
FTGA-DDNN (2h)	35	40	45

Modeling the drift of nanomaterials and choosing a suitable one that performs more robustly over time are two strategies to apply these methods in the longer term without having to modify them. To perform this, we monitored the transmittance change for nanomaterial filters for at least 400 days. Subsequently, an exponential curve was fitted to the average transmittance values for each filter at every frequency concerning the number of weeks after the optics was manufactured.

5. CONCLUSION

In conclusion, established that the spectral range of any narrow-band reflected light in the nanomaterial spectrum can be specifically calculated using several types of DL approaches using a transmitted substance derived from a limited number of inexpensive nanotube impacts that require minimal supervision throughout manufacturing. DL model is more dependable because of its improved resilience to noise and environmental variations. The model can better manage fluctuations in input data through the development of responsive visualizations, which increases its recognition efficiency. It initiates an accumulation of responses to Fine-Tuned Genetic Algorithm Based Dynamic Deep Neural Network (FTGA-DDNN) and promotes their expansion and improvement. One important component that has contributed to increasing overall system dependability is the model's capacity to distinguish between real signals from nanomaterial and interference. Furthermore, monitoring constant changes in the filter functions; findings validate the feasibility of simulating the steady drifting of nanoparticles.

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Покращення впровадження та надійності детекторів на основі наноматеріалів за допомогою методу глибокого навчання

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Підвищення надійності та впровадження мають вирішальне значення в реальних програмах, і властива непередбачуваність нематеріалів ускладнює інтеграцію детекторів наноматеріалів (НМ) у ці середовища. Надійні припущення можуть бути побудовані на основі даних, створених такими датчиками, за допомогою глибокого навчання (DL), що є потужним методом. У цьому дослідженні ми запропонували новий метод під назвою «Динамічна глибока нейронна мережа на основі тонко налаштованого генетичного алгоритму» (FTGA-DDNN), навчання якого є дорогим з обчислювальної точки зору, але він дає найефективніший результат при оцінці в Інтернеті, зберігаючи розумний рівень надійності. . Це може бути корисним у середовищах, що динамічно змінюються, де алгоритму потрібно досліджувати нові можливості, одночасно використовуючи відомі рішення. Завдяки оптимізації DL метою покращення реалізації та надійності детекторів наноматеріалів є підвищення їх адаптивності та ефективності в

різноманітних ситуаціях. Ми представляємо порівняльний аналіз результатів, отриманих із запропонованої нами методики, з іншими існуючими методами. Наші висновки вказують на високу продуктивність у середній похибці, середній абсолютній похибці та часу напівлогарифмічного тестування, демонструючи ефективність підходу FTGA-DDNN. Підсумовуючи, це дозволяє нам прогнозувати та прогнозувати функцію фільтра пізніше, підвищуючи точність алгоритмів DL та корисність фільтрів протягом тривалих періодів.

Ключові слова: Глибоке навчання (DL), Наноматеріали (NM), Нанотехнології, Динамічна глибока нейронна мережа на основі точного налаштування генетичного алгоритму (FTGA-DDNN).