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# Deep convolutional neural network based Henry gas solubility optimization for disease prediction in data from wireless sensor network

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**Abstract**

In the fight against COVID-19, this study explores clinical image processing and deep learning for effective solutions. Emphasizing collaboration between scientists and policymakers, it addresses data reliability issues and sparse experimentation, critical for accurate COVID-19 identification and mitigation of underreported cases. The proposed

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Henry Gas Solubility (HGS) optimized Deep Convolutional Neural Network (DCNN) enhances prediction accuracy and computational efficiency, validated through rigorous experiments. The study highlights the importance of integrating diverse datasets and outlines future research directions, highlighting its potential impact on healthcare decision-making and pandemic response strategies.

***Subject Classification:*** *68T07, 68U10.*

***Keywords:*** *Wireless sensor network (WSN), Deep convolutional neural network (DCNN), Image processing, Henry gas solubility (HGS), COVID-19.*

## 1. Introduction

All areas of science are heavily investing in the fight against the COVID-19 pandemic, with clinical image processing techniques and deep learning (DL) being investigated as viable long-term treatments. This study, which highlights existing issues and covers the way for future research paths, stresses the application of deep learning and image registration approaches in COVID-19 identification in a novel way [1]. It suggests advice for the scientific community and politicians to strengthen efforts against the disease, drawing upon credible publications [2]. Unreliable data and few experiments pose a significant hurdle to COVID-19 research, leading to unreported illnesses and deaths. It's unknown if any cases possibly thousands were missed in the virus's detection process [3]. Comprehensive information about the virus's prevalence in the general population has not been released by any nation. Medical research must proceed despite these obstacles, highlighting the need for data fusion [4].

Integrating data from several sources to improve entity categorization, identification, and detection is known as knowledge fusion. Depending on big, high-quality datasets is essential for machine learning and deep learning to produce correct results [5]. CNN was used to merge datasets from Italian Society for Medical and Interventional Radiology (SIRM) in conjunction with GitHub X-ray pictures for the detection of COVID-19 [6]. In data shortages, knowledge fusion makes accurate forecasts possible, which are essential for making prompt decisions when medical facilities are under pressure during outbreaks. Because of COVID-19's rapid growth and potential for catastrophic results, early identification and management are critical and may require urgent decisions with limited resources [7].

After an extensive background review, limited research on COVID-19 case prediction was found. The pandemic's global impact highlights sustainability and survival concerns due to its highly contagious nature

[8]. Early detection and prevention are critical to halt its spread, requiring fast and accurate diagnosis methods. Machine learning techniques offer solutions to traditional challenges such as resource constraints, long detection times, and rigorous cleaning protocols [9]. Emphasizing ML approaches can enhance disease containment efforts and reduce mortality rates. This study introduces a Henry Gas Solubility (HGS) model based on DCNN for COVID-19 forecasting [10]. The equilibrium of the study is arranged as specified: part 2 defines related works, section 3 explains the preliminaries and the suggested method presented, and Section 4, the experimental investigations conducted. Finally, section 5 brings the article to a close.

## 2. Related work

The researcher proposed Sensor Network Tomography (SNT) to virtualize sensor network health scans efficiently [11]. SNT uses localized methods to combine localized scan data in-network, reducing communication and processing costs by aggregating local scans into a composite representation rather than gathering precise information from each node individually. In a Cluster-based WSN, a Secure Image Processing and Transmission Scheme (SIP-TS) was introduced. Unlike existing secure data transfer schemes that focus on text data, SIP-TS addresses the challenge of secure image communication in WSNs [12]. This is crucial for applications like military operations where image data is critical but sensor nodes have limited resources and operate in unattended environments. SIP-TS utilizes Elliptic Curve Cryptography (ECC) and Homomorphic Encryption (HE) to ensure secure transmission and processing of images in WSNs. Researchers proposed a wireless sensor network privacy model based on fake sources. They established the NP-completeness of the false sources problem, developed parameterized algorithms for three network configurations, and demonstrated that these heuristics achieve optimal levels of Source Location Privacy (SLP) when appropriately parameterized [13]. The study highlights that fake sources can significantly enhance SLP levels, marking a theoretical advancement in privacy protection for sensor networks. For the wearable WSN, the researcher suggested a Deep Learning (DL) model to safeguard the Big Data psychoanalytic plan in isolation. This study showed ways to use deep learning to monitor and analyze patient health data, collect data from sensors, and prevent illness by sending out timely alarms [14]. The results of rigorous analysis and experiments confirm the security and efficiency of the DL approach. The SEIRS-V model was introduced to study disease dynamics. When the reproduction rate is less than one, the infected nodes diminish over time; if it's greater than one, the infection persists. Numerical methods are employed to solve and validate the system of equations, crucial for understanding epidemic equilibrium and implementing security protocols in WSN [15].

## 3. Methodology

The DCNN architecture comprises three main components: a shared sub-network layer, a direction estimation layer and a detection layer. It utilizes an hourglass structure to capture multi-level features for pixel-wise prediction. The network employs ResBlocks for downsampling and maintains feature map dimensions with padding. An encoding-decoding path, enhanced by sub-pixel components, doubles the feature map's resolution. The architecture integrates convolutional layers with ReLU activation and batch normalization, preserving spatial information throughout the hourglass network. The detection layer outputs the likelihood rate for each pixel. It uses an upsampling decoder with de-convolution techniques. The detection branch includes a sigmoid layer, a 1×1 convolutional layer, and a batch normalization layer to reduce computing time, with a sigmoid function generating the location map as shown in Figure 1.

Stimulated by Henry's law of gas solubility in liquids, the Henry Gas Solubility Optimization (HGSO) method simulates gas behavior and solubility dynamics to address optimization challenges. HGSO updates

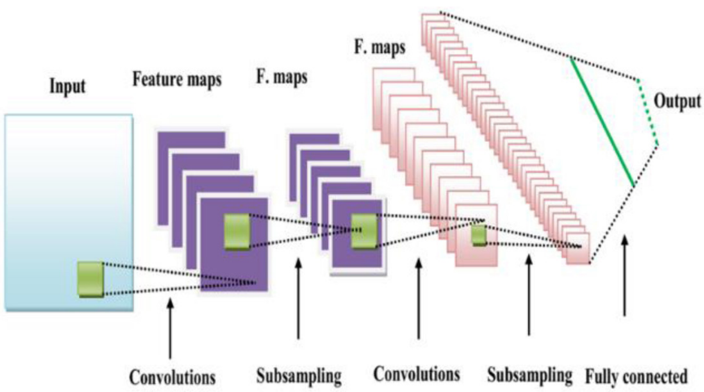


**Figure 1**

**The general DCNN Framework**

Henry's coefficients based on environmental conditions, initializes gas locations and constants, groups agents by gas types, and optimizes solubility and positions through iterative procedures. It effectively avoids local optima in complex problems by balancing exploration and exploitation. The algorithm, based on Henry's law proposed by William Henry in 1803, maintains that the ability of a gas to dissolve in a liquid is closely correlated with its partial pressure at persistent temperature. Henry's law expressed in equation form is:

$$G_{sol} = HE \times G_{press} \tag{1}$$

This equation determines low-soluble gases' solubility in liquids. Temperature and pressure are critical factors influencing solubility; higher pressures increase gas solubility. The medical cloud ensures both trustworthiness and curiosity in handling encrypted data for meaningful insights. Server clusters are overseen by local health authorities. Sensors track heart rates and medication levels, gathering health data such as age and heartbeat (Figure 2). DCNN-HGS algorithms predict symptom likelihood. Mobile alerts are sent via phones, and GPRS tracks patient locations within hospital networks. Energy-efficient routing algorithms optimize network longevity in emergencies.

Figure 2 depicts sensors gathering personal health data, encrypted by a helper node before transmission to a cloud server. At the cloud server, Using DCNN-HGS techniques, data is decrypted for illness prediction. Sensor data undergoes homomorphic encryption, enabling computations without decryption. Encrypted data is securely processed in commercial

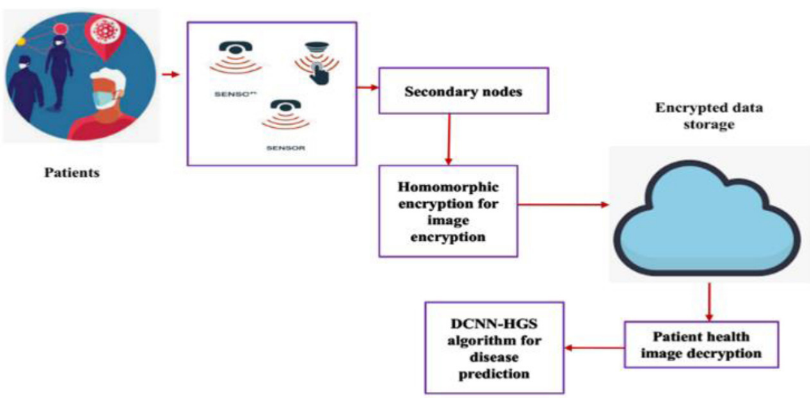


**Figure 2**

**System architecture**

cloud environments, evaluating encryption algorithm efficiency and compatibility. During training, cloud-stored encrypted data supports disease prediction and alerts medical staff. Wearable sensors encrypt health data for upload to medical cloud storage, ensuring privacy via inaccessible decryption without a private key. The DCNN-HGS algorithm predicts COVID-19 disease, starting with image pre-processing to enhance quality, feeding pre-processed data into the DCNN framework. Optimizers adjust weights and learning rates crucially, optimized via an HGS algorithm. Addressing minimal diversity, a mutation sub-program enhances randomization and search direction beyond traditional HGSO methods. The mutation sub-program introduces a threshold circumstance, as the equation shows:

$$TH = (1-(x-1)/MG-1))^{\frac{1}{\psi}} \tag{2}$$

Where MG is the maximum number of generations, TH is the threshold value, and ψ is the mutation aspect. When an arbitrary number drops below TH, the mutation sub-program triggers, generating a novel location randomly among the problem's lesser and upper bounds. Figure 3 illustrates the suggested disease prediction DCNN-HGS algorithm, classifying COVID-19 patients into normal and abnormal categories based on the model's predictions.

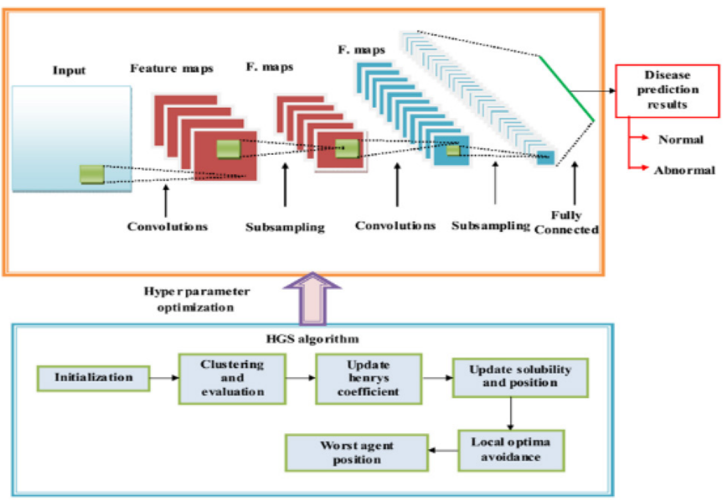


**Figure 3**

**A suggested HGS algorithm for illness prediction based on DCNN**

## 4. Experimental result and analysis

The CC2420-enabled MICAz platform was chosen because of its affordability and wide availability. Each sensor sends all of the RSSI data from all other sensors thanks to specially designed software written in nesC and TinyOS. All of these messages were intercepted by a base station and forwarded to a computer for additional management. Table 1 displays the experimental conditions.

**Table 1**

**Experimental settings.**

| Parameters | Value |
|---|---|
| Communication range | 20 (for small) and 75 (for large) |
| Number of nodes | 150, 200, 250, and 300 |
| Number of localized nodes | 10-30 |
| Number of iterations | 5 |
| Number of search agents | 50 |

Due to a shortage of medical resources and personnel, countries like India and Brazil have seen a surge in COVID-19 cases. To address this, they are using an HGS-optimized DCNN architecture within a Wireless Sensor Network (WSN). Diagnosis relies on SARS-CoV-2 CT scan datasets and real-time WSN sensor data. They set aside 20% of the data for testing and 80% for training. The model's accuracy is assessed by minimizing the error rate, using the Principal Minimum Cross-Entropy (PMCE) method with a likelihood loss function to evaluate the variance among predicted (a`) and actual outputs (a).

$$PMCE = -\sum_{o=1}^{M} a_{o,c} \, log \, log \, (a_{o,c}) \tag{3}$$

In the given equation, $M$ represents the total count of features that were input, $o$ denotes the experiential value for a specific class, $a$ represents the predicted probability value, and log denotes the logarithmic function. The resulting loss function is derived accordingly.

$$Loss = -\frac{1}{m}\sum_{o=1}^{m} log \, log \, (m^{(c)}) \tag{4}$$

Using the equations provided, deviations between actual and predicted outputs are computed, as summarized in Table 2 during at least five transmissions. In Table 2, the suggested approach accomplishes a minimum PMCE (Principal Minimum Cross-Entropy) value of 0.014 and a maximum PMCE value of 0.65. Comparatively, PMCE is attained by deep learning, SNT, and SEIRS-V values of 0.037, 0.056, and 0.037 respectively at the fifth transmission. A lower PMCE value, such as 0.014 achieved by the proposed methodology, indicates effective detection and reduction of incorrect predictions. The HGS-optimized DCNN proposed here exhibits the lowest rate of 0.018 for the loss function, outperforming existing techniques like SEIRS-V (0.024), SNT (0.037), deep learning (0.037), and SIP-TS (0.035) across five iterations.

**Table 2**

**Analyzing differences using PMCE and loss function.**

| Techniques | Number of transmissions for PMCE | | | | | Number of transmissions for Loss function | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| Deep learning | 0.02 | 0.03 | 0.04 | 0.043 | 0.037 | 0.0453 | 0.03 | 0.04 | 0.043 | 0.037 |
| SNT | 0.023 | 0.023 | 0.04 | 0.045 | 0.056 | 0.040 | 0.023 | 0.04 | 0.045 | 0.037 |
| SIP-TS | 0.012 | 0.025 | 0.0026 | 0.036 | 0.065 | 0.026 | 0.025 | 0.0026 | 0.036 | 0.035 |
| SEIRS-V | 0.028 | 0.027 | 0.029 | 0.033 | 0.037 | 0.029 | 0.027 | 0.029 | 0.033 | 0.024 |
| Proposed HGS optimized DCNN | 0.0012 | 0.018 | 0.017 | 0.016 | 0.014 | 0.0022 | 0.017 | 0.023 | 0.021 | 0.018 |

The many performance indicators that were employed to assess the suggested technique's efficacy are provided below:

$$Precision = \frac{True\_positive}{True\_positive + False\_positive} \tag{5}$$

$$call = \frac{True\_positive}{True\_positive + False\_negative} \tag{6}$$

$$F1 - score = 2 \bullet \frac{precision \bullet recall}{precision + recall} \tag{7}$$

The F1-score, recall, and precision of the proposed methodology are compared in Table 3, with the state-of-the-art methods, including Deep learning, SNT, SIP-TS, and SEIRS-V, across a minimum of ten transmissions. The suggested method produces F1-score, recall, and precision values of 98.36%, 98.21%, and 98.12%, respectively. SEIRS-V follows closely with F1-

score values, recall, and precision of 98.36%, 98.21%, and 98.12%. SIP-TS, SNT, and deep learning rank lower in performance. The DCNN-HGS demonstrates its effectiveness in detecting anomalies in deep-ranging sensor networks through rigorous training and testing. The HGS algorithm significantly enhances the accuracy of detecting malevolent nodes, delivering superior outcomes with minimal error deviation. The proposed DCNN-HGS achieves a maximum accuracy of 98% in identifying abnormalities, highlighting its robust recognition capabilities.

**Table 3**

**Evaluation by comparison among various methods.**

| Methods | Accuracy (%) | Recall (%) | F1-score (%) |
|---|---|---|---|
| Deep learning | 95.32 | 95.43 | 95.64 |
| SNT | 96.32 | 96.45 | 96.78 |
| SIP-TS | 97.43 | 97.93 | 97.65 |
| SEIRS-V | 98.51 | 97.76 | 97.21 |
| Proposed HGS optimized DCNN | 98.36 | 98.21 | 98.12 |

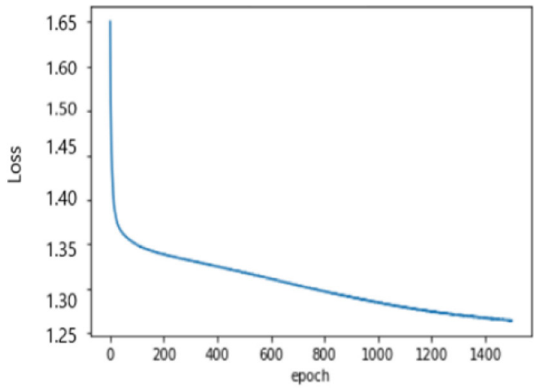


**Figure 4**

**Training Loss**

The Matlab-simulated RSSI-based location algorithm spans a 120 × 120 m area with 20 sensing nodes and 80 malicious nodes, each with a 30-meter communication radius. Figure 4 shows the training loss graph for a model trained on 1,974,856 samples across 1500 epochs. Security assessment involves 10 WSN nodes monitoring wireless device behavior. The DCNN-HGS model effectively identifies diverse node behaviors,

**Table 4**

**Comparison of the computational time outcomes**

| Methods | Computational time (s) |
|---|---|
| Deep learning | 8.3 |
| SNT | 13.23 |
| SIP-TS | 11.34 |
| SEIRS-V | 8.2 |
| Proposed | 3.2 |

focusing on malicious activities through penetration rate analysis. Attack types include a 1.9-second normal attack and a 3.64-second intelligent attack using sampling, swapping, and micro-aggregation targeting smart vehicles and mobile phones. Tracking technologies enable behavior prediction and influence, posing privacy concerns amidst data misuse and sharing gaps in user education.

Table 4 compares the computational time of the proposed methods with existing methods like SEIRS-V, SNT, SIP-TS, and deep learning. The new technique demonstrates significantly faster computation, taking only 3.2 seconds compared to other methods. This efficiency makes it a more cost-effective option. Security performance is evaluated with different node numbers (75, 150, and 250), and the proposed method consistently outperforms security results, deep learning, SNT, SIP-TS, and SEIRS-V.

## 5. Conclusion

This study introduced a DCNN optimized with HGS for predicting COVID-19 disease. The DCNN-HGS system gathers sensor data to assess ongoing health conditions and predict diseases, providing timely alerts. They implement a secure data deletion method to safeguard health data privacy, allowing owners to restrict access to particular user health information. To demonstrate the reliability and effectiveness of the approach, they present extensive analytical and experimental data, comparing its performance with existing systems. Simulation outcomes demonstrate that the method achieves highly reliable and accurate node positioning in wireless sensor networks (WSNs) compared to current approaches. The normal attack employs a random noise method, taking approximately 1.9 seconds to execute, while an intelligent node requires 3.64 seconds for a similar attack.

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