The Scientific Temper (2024) Vol. 15 (4): 3281-3289
E-ISSN: 2231-6396, ISSN: 0976-8653
Doi: 10.58414/SCIENTIFICTEMPER.2024.15.4.37
https://scientifictemper.com/

RESEARCH ARTICLE

A blockchain-integrated smart healthcare framework utilizing dynamic hunting leadership algorithm with deep learning-based disease detection and classification model

Lakshminarayani A*, A Shaik Abdul Khadir

Abstract

The healthcare sector has embraced a digital revolution driven by modern technology. Smart healthcare solutions improve patient care by addressing the challenges of traditional methods using large-scale sensor devices. Blockchain (BC) technology ensures secure, decentralized storage and sharing of medical data, fostering intelligent healthcare ecosystems. Robotics and machine learning (ML) also benefit from shared medical data. This manuscript introduces a blockchain-integrated smart healthcare framework utilizing a dynamic hunting leadership algorithm for deep learning-based disease detection and classification (BSHDHL-DLDDC). It focuses on accurate disease diagnosis using deep learning on medical images. BC technology enables secure, tamper-proof storage and privacy-compliant data sharing. Adaptive bilateral filtering (ABF) reduces noise while preserving key image details. An enhanced CapsNet model captures spatial relationships for improved feature extraction. A bi-directional gated recurrent unit (BiGRU) classifier detects and classifies diseases, with performance refined via a dynamic hunting leadership (DHL) algorithm. Simulations confirm the framework's effectiveness, demonstrating better results compared to existing methods.

Keywords: Blockchain, Dynamic hunting leadership, Smart healthcare, Disease detection, Deep learning, Feature extractor.

Introduction

Smart healthcare is the progress of typical healthcare with modern internet technologies. It incorporates various technologies to process health-related data collected from patients using smart wearable devices and to detect health issues in real time from the gathered information (U. Bodkhe, P. Bhattacharya, S. Tanwar, S. Tyagi, N. Kumar, and M. Obaidat 2019). This involves leveraging spreads in the internet and communication structure with big data technologies to deliver telemedical patient-centered maintenance. A significant fragment of health and medical services is the usage of medical images at dissimilar phases of disease analysis, management, and treatment (I. Mistry, S. Tanwar, S. Tyagi, and N. Kumar, 2020). In this method, medical images are kept, conveyed, and analyzed to aid clinicians and other professionals on different sides of patient care. This efficacy has made medical images and other electronic health records (EHR) the target of ill-treatment, forbidden tampering, and other criminal actions (Nouman, A. and Muneer, S., 2022). Therefore, medical images are very vital for effectual patient care, and attempts to safeguard their confidentiality, integrity, and availability (CIA) earn every support (V, Nyemeesha., Kavitha, M. Skin Lesion 2024). The healthcare sector has developed by expanding the usage of novel technologies like the Internet of Things (IoT), machine learning (ML), and blockchain (BC) technology. BC can have a superior impact on the medical research area of healthcare since BC permits for sharing, storing, and tracking of data (Lobo, V.B., Analin, J., Laban, R.M. and More, S.S., March 2020). This BC method can upsurge the credibility of medical studies, which has been frequently smeared owing to numerous scandals (Anand, R., Kareem, S.F., Mubeen, R.M.A., Ramesh, S. and Vignesh, B., October, 2021). At present,

[1]Department of Computer Science, Khadir Mohideen College, Adirampattinam, Affiliated to Bharathidasan University, Tamil Nadu, India.

***Corresponding Author:** Lakshminarayani A, Department of Computer Science, Khadir Mohideen College, Adirampattinam, Affiliated to Bharathidasan University, Tamil Nadu, India, E-Mail: lakshminagakarthick@gmail.com

How to cite this article: Lakshminarayani. A., Khadir, A.S.A. (2024). A blockchain-integrated smart healthcare framework utilizing dynamic hunting leadership algorithm with deep learning-based disease detection and classification model. The Scientific Temper, **15**(4):3281-3289.

Doi: 10.58414/SCIENTIFICTEMPER.2024.15.4.37

Source of support: Nil

Conflict of interest: None.

Received: 10/10/2024 **Accepted:** 06/11/2024 **Published** : 20/12/2024

BC technique has shown an effectual solution to attain computation efficiencyand higher security when equated to the traditional cryptography solution for cloud data processing. So, BC has become a critical technology for developing healthcare 4.0 standards (S. Tanwar, K. Parekh, and R. Evans 2020). In the field of healthcare, a delicate changeover is arising, stimulated by electronic health record (EHR) methods, real medicinal data-collecting through wearable entities, artificial intelligence (AI), and enlarged data understanding. A better solution to these issues derives from the execution of BC, permitting transactions through decentralization. The complex method of the healthcare industry poses further challenges to executing BC technology (C.-Y. Li, X.-B. Chen, Y.-L. Chen, Y.-Y. Hou, and J. Li 2019). Medical sensors and devices gather a vast volume of data, which are employed in order to categorize and predict diseases in healthcare depending upon ML methods. Furthermore, systems based on ML are trained utilizing big data to help healthcare employees in risk treatment and assessment. These methods remove the human component from the method, decreasing errors (S. Shamshad, Minahil, K. Mahmood, S. Kumari, and C.-M. Chen 2020). The incorporation of ML with IoT devices enables the management, analysis, and monitoring of medical reports. The IoT-enabled applications that combine BC technologies with ML techniques can aid in infectious illness tracking and drug traceability (H. Huang, P. Zhu, F. Xiao, X. Sun, and Q. Huang 2020). This manuscript focuses on the design and development of a blockchain-integrated smart healthcare framework utilizing a dynamic hunting leadership algorithm for deep learning-based disease detection and classification (BSHDHL-DLDDC) model. To accomplish this, the BSHDHL-DLDDC technique applies an adaptive bilateral filtering (ABF) approach to effectively reduce noise while preserving important edges and details in medical images. For the feature extractor process, the improved CapsNet model can be employed, capturing intricate spatial relationships within the images to enhance diagnostic precision. In addition, the bi-directional gated recurrent unit (BiGRU) classifier is performed to detect and classify disease. To improve the classification performance of the BiGRU classifier, the parameter tuning process is performed through a dynamic hunting leadership (DHL) algorithm. A wide range of simulation studies is carried out to ensure the implication of the BSHDHL-DLDDC technique.

Related Works

In (Gajndran, S., Muthusamy, R., Ravi, K., Chandraumakantham, O. and Marappan, S, (2024)), a new elliptic crypt with a secured BC-backed federated Q-learning framework has been introduced. Primarily, the IoMT data was gathered from openly accessible databases and encrypted with the extended elliptic curve cryptography (E_ECC) approach to guarantee safety. These encoded data are provided for the input to the BC-powered cooperative learning approach. Next, the data was safely deposited in decentralized BC technologies. In (Albakri, A. and Alqahtani, Y.M. (2023)), an IoMT with a BC-based smart healthcare system with encryption by optimal DL (BSHS-EODL) approach was developed.

The introduced model contains image encryption, data collection, and data classification. Firstly, the IoMT tools allow the collection of data procedures, and the collected images are deposited in BC for safety. Next, image encryption has been utilized for data encryption, and its important generation model was carried out through the dingo optimizer algorithm (DOA). Lastly, the BSHS-EODL approach implements analysis of disease, including voting ELM (VELM), SqueezeNet, and Bayesian optimization (BO)-based tuning of the parameter. Mohammed *et al*. Mohammed, M.A., Lakhan, A., Zebari, D.A., Abd Ghani, M.K., Marhoon, H.A., Abdulkareem, K.H., Nedoma, J. and Martinek, R., (2024) proposed a new Pattern-Proof Malware Validation (PoPMV) model intended for BC in ICPS. The work additionally uses a DL algorithm (LSTM) with reinforcement learning methods for receiving rewards and feedback in real-time. The major aim is to mitigate securities vulnerability, improve handling speed, recognize either unfamiliar or familiar attacks, and enhance the ICPS functionalities.

Li, J., Li, D. and Zhang, X., (2023) implemented a secured BC-helped access controller system for SHS in fog computing. Every user process are verified on the BC by smart contract to guarantee the reliability and transparency of the method. This paper moreover provided a BC-helped multi-authority attribute based encryption (MA-ABE) model using keyword search to ensure data confidentiality, preventing single failure points and performing fine-grained access control of the system. Chatterjee *et al*. Chatterjee, S., Bhattacharya, P. and De, D., (2024) introduced an architecture, LightDew, which utilizes the Dew Computing (DC) paradigm in Smart Assisted Living (SAL) environments. DC permits efficient communication, lower resource usage, and real-time decision-making abilities. Initially, at dew layer, a shallow neural network approach has been presented that is termed a lightweight activity recognition (LAR) algorithm. The LAR outputs are safely signed and hashed with the lightweight secp256k1 curve, which guarantees data authentication and integrity.

Raju *et al*. Raju, K., Ramshankar, N., Shathik, J.A. and Lavanya, R., (2023) developed a secure outsourcing system using a DL structure was implemented. Firstly, the healthcare data was gathered from the normal datasets, and this can be encoded with the optimal key-based hybrid ECC with fully homomorphic encryption (OK-HECCFHE). Formerly, the encoded data was deposited within the BC, and it becomes decoded by the proper user by the optimum key. Lastly, the healthcare data prediction has been completed through the Optimized DNN with GRU (ODNN-GRU). In Govindaram, A. and Jegatheesan, A., (2024), a BC-aided deep federated learning (BC_DFL) model was applied

for detecting intruders. The three important processes utilized in the presented intrusion detection framework are intrusion detection, pre-processing, and data collection. Data reduction, normalization, transformation, and cleaning are applied in pre-processing to extract unimportant information and increase data quality. This pre-processed data has been directed to the BC_DFL model for intrusion detection.

Proposed Methodology

In this manuscript, we focus on the design and development of the BSHDHL-DLDDC model. The main goal of the BSHDHL-DLDDC method is to utilize deep learning techniques for accurate disease diagnosis from medical images. It contains four distinct kinds of processes illustrated in Figure 1.

Blockchain in Smart Healthcare Systems

The integration of BC technology ensures decentralized, tamper-proof storage of medical records, allowing secure sharing between healthcare providers while retaining patient privacy. A lot of efforts were completed attempt to discover a balance between data privacy and the necessity for providers and patients to utilize these delicate data for several reasons Healthcare Engineering, J.O., 2023. In Particular, with the extensive usage of the IoT in EHRs, it turns out to be simpler to gather data from various sources on multiple metrics at single positions.

To attain this, we use smart contracts in an ethereum-based BC to control admittance to complex information of patients and a progressive cryptography approach to guarantee safety. Based on the authors, the execution of this solution will permit patients to control their EHRs, whereas healthcare organizations may utilize the sensitive data of patients suitably without revealing their privacy. After a similar philosophy, a framework concentrating on healthcare IoT has been recommended. Over the acceptance of BC and cryptographic models for ensuring privacy, the main particularities of these solutions are that sensitive information has been managed within the hospital whereas accessing was accomplished depending on the part of users. Moreover, to offer transparency in healthcare activities, smart contracts have been applied for recording each event. In this context, the authors presented a BC-based and privacy-preserving system named Healthchain, permitting patients to efficiently control admission to their data by adding or canceling approved physicians by utilizing user transactions for strategic management. Consequently, the authors presented a patient-centered medical data management method whereas the BC has been applied as storage to achieve privacy. Hence, we presented SmartMedChain, which contains ServiceChain, LogChain, and DataChain to attain protection of privacy concerning various -healthcare shareholders.

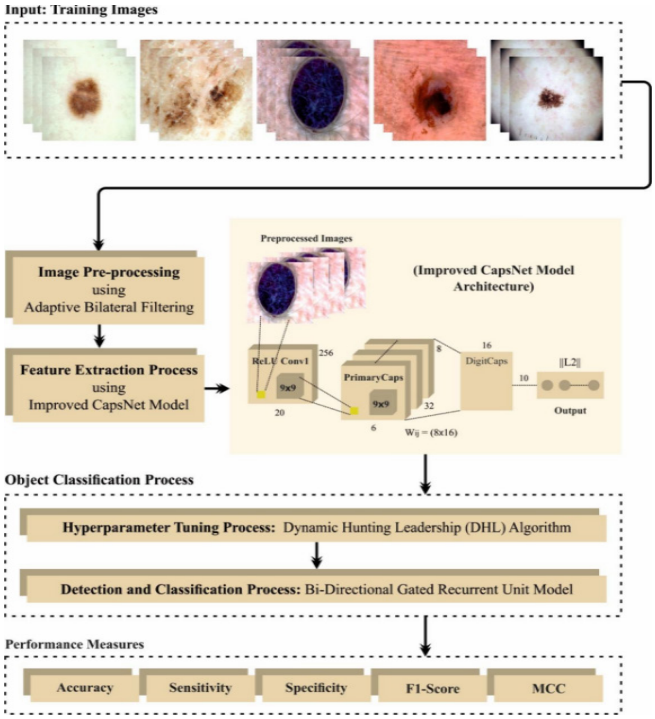

Figure 1: Overall process of BSHDHL-DLDDC model

ABF based Image Pre-processing

Primarily, the BSHDHL-DLDDC technique applies an ABF approach to effectively reduce noise while preserving important edges and details in medical images. ABF is a vital pre-processing method in disease recognition in smart healthcare systems, particularly for the enhancement of the medical image Yu, H., He, F. and Pan, Y., 2020. It efficiently decreases noise while upholding significant features, like textures and edges, in imaging data. By altering the filtering parameters depending on local image features, this model certifies that major details that are vital for precise diagnosis are preserved. The enhanced image quality permits more consistent analysis and feature extraction, most important to better disease recognition outcomes. Eventually, ABF improves the performance of DL algorithms, enabling appropriate and precise medical decision-making.

Improved CapsNet Feature Extractor

For the feature extractor process, the improved CapsNet model can be employed, capturing intricate spatial relationships within the images to enhance diagnostic precision.

CapsNet is a new structure, which generates neurons united in a novel method of unit Wang, B., Wang, L., Xu, W., Ren, H. and Cheng, W., 2024. Every capsule has many neurons that can be encoded as activation vectors. The CapsNet structure was presented to learn numerous properties of signals, which can reflect the comparative location information among the discriminative features mined by the preceding convolution

module. First, a dynamic routing mechanism was employed as routing-by-agreement among capsules to direct capsules to their match parent. In this mechanism, every preceding capsule layer is increased by a matrix of weight, and then every vector is biased by the coupling coefficient to acquire the existing outcome. Next, the coupling coefficient is iteratively advanced by evaluating the constancy among every prediction vector and present output for generating the final output vector. Presently, attention mechanisms have attained extraordinary achievement in numerous domains like speech recognition, image classification, NLP, and computer vision (CV). The attention mechanism pretends this attention of human distribution mechanism, by providing the capability to pay attention to input data, it can better comprehend and handle the data. The self-attention structure permits one to learn weights among capsules more intensely and evades the iterative routing control method. The improved CapsNet module contains dual layers, such as primary and digital capsule layers. In the primary capsule layer, the output of the preceding convolution module is initially redesigned and transformed into the method of capsules. To exemplify the self-attention mechanism routing technique, let's take a capsule vector in the digital capsule as an instance. Assume that the matrix of the primary capsule layer, which represents the amount of capsules, signifies the embedded vector in the capsule and means the dimensional. Initially, every capsule vector is increased by a weight matrix to get prediction vectors:

$$\hat{u}_{j|i} = W_{ij} u_i \qquad (1)$$

Here $i = 1, N, j = 1, \ldots, M, M$ represents the amount of capsules. In this paper, $M = 4$. It is noticeable that $N \times M$ distinct weight matrices are employed. The matrix is linearly altered to get key (K) and query (Q). They are mathematically modeled below:

$$Q = UW^{Q} \in \mathbb{R}^{N \times P} \qquad (2)$$

$$K = UW^{K} \in \mathbb{R}^{N \times P} \qquad (3)$$

Here $W_j^Q \in \mathbb{R}^{N \times P}$ and $W_j^K \in \mathbb{R}^{N \times P}$ and are matrices of dimensional parameters. Next, the dot product is used over Q and K for evaluating the relationship, and the outcome is passed done a softmax function to get the attention weights. It is mathematically expressed below:

$$A = softmax\left(\frac{QK^{T}}{\sqrt{D}}\right) \qquad (4)$$

While, $A \in \mathbb{R}^{N \times N}$ refers to an attention weight matrix. Then, the matrix of attention score is weighted on "prediction vector matrix" $\hat{U}_j = \left[\hat{u}_{j|1}, \hat{u}_{j|2}, \ldots, \hat{u}_{j|i}, \ldots, \hat{u}_{j|N}\right]^T$ with dot product and totalled to make the capsule. This stage is expressed below:

$$s_j = \sum_{i=1}^{N} (A\hat{U}_j)_i \qquad (5)$$

Lastly, non-linear squashing function is used to squash to certify an output vector among and one

$$\boldsymbol{v}_j = \frac{\| \boldsymbol{v}_j \|^2}{1 + \| \boldsymbol{v}_j \|^2} \frac{\boldsymbol{v}_j}{\| \boldsymbol{v}_j \|} \qquad (6)$$

Here, v_j indicates the likelihood of its corresponding class.

Classification using BiGRU Model

In addition, the BiGRU classifier is performed to detect and classify disease. The GRU is a kind of recurrent neural network (RNN), which utilizes a gating mechanism to choose what data passes to the output, thus extracting out irrelevant data Mao, R., Lee, J.E. and Edwards, M.C., 2024. Standard RNNs experience the problem of vanishing gradient, where the inclines of the loss function become near zero and are back-propagated over the neural networks. GRUs can evade this problem by utilizing reset and update gates to control the flow of data, permitting them to acquire long-term time dependencies. GRUs are speedier than LSTMs in low-difficulty sequences.

The reset gate defines how much data from the historical hidden layer (HL) must be forgotten. It outputs a value among and 1, where indicates forg *et al*l and 1 means recollect all. The output is employed in order to define a candidate HL, or the novel information. The update gate governs how much weight to adorn past HL and how much weight to adorn candidate HL. It outputs a number between and 1, where means putting each weight on the preceding HL, and 1 states that it puts each weight on the candidate HL. The typical GRU formulations were expressed as follows:

$$r_t = sigmoid\left(W_r x_t + U_r h_{t-1} + b_r\right) \left(Reset\ gate\right) \qquad (7)$$

$$z_t = sigmoid\left(W_z x_t + U_z h_{t-1} + b_z\right) \left(Update\ gate\right) \qquad (8)$$

$$\hat{h}_t = tanh\left(W_h x_t + U_h \left(r_t \odot h_{t-1}\right) + b_h\right) \left(Candidate\ HL\right) \qquad (9)$$

$$h_t = \left(1 - z_t\right) \odot h_{t-1} + z_t \odot \hat{h}_t \left(Updated\ HL\right) \qquad (10)$$

For this neural network, the trainable parameters are . In addition to the typical GRU, theBiGRU improves the model's capability to arrest context from both future and past states. Dual separate GRU layers are employed in the BiGRU layer: one handles an input sequence in a forward direction, while the other processes it backward.

$$\vec{h}_t = GRU_f\left(x_t, \vec{h}_{t-1}\right) \left(Forward\right) \qquad (11)$$

$$\overleftarrow{h}_t = GRU_b\left(x_t, \overleftarrow{h}_{t+1}\right) \left(Backward\right) \qquad (12)$$

$$h_t^{bi} = \left[\vec{h}_t ; \overleftarrow{h}_t\right] \left(Combined\ BiGRU\ output\right) \qquad (13)$$

This structure permits the system to use data from both directions, enhancing performance on tasks that profit from realization of the time dependence near every input. Figure 2 depicts the structure of BiGRU.

Hyperparameter Tuning Process

To improve the classification performance of the BiGRU classifier, the parameter tuning process is performed through DHL algorithm.

Social Hierarchy

In the DHL algorithm, the social hierarchy is explained by presenting dual variables and to signify the amount of leaders a hunter evaluates for location upgrades and the total volume of hunters, correspondingly Adegboye, O.R., Feda, A.K., Ojekemi, O.S., Agyekum, E.B., Elattar, E.E. and Kamel, S., 2024. The efficiency of every hunter's solution is taken into consideration when choosing the leaders. Particularly, till every leaders are selected, the hunter with the finest fitness value is nominated as the 1st leader, followed by the predator with the 2nd-excellent fitness value, and many. In the hunting, every hunter's position vector is set by , and means an objective value, which specifies the hunter's proximity to the most susceptible prey. and signify the locations of a leader and the prey. The leaders are classified on how close they are to the victim, with the finest leaders being those who are closest to the objective.

Hunting Process Of A Prey

Generally, hunters use to encircle some prey, and every targeted prey resembles to problem's local goals. The mathematical formulation of the encircling method is mentioned below:

$$\vec{X}_{it+1} = \vec{X}_p - \mu \cdot (2 \cdot r_1 - 1) \cdot \left| \vec{r}2 . \vec{X}_p - \vec{X}_{it} \right| \quad (14)$$

$$\mu = 2 - \frac{(2 \cdot it)}{\text{Max\_}it} \quad (15)$$

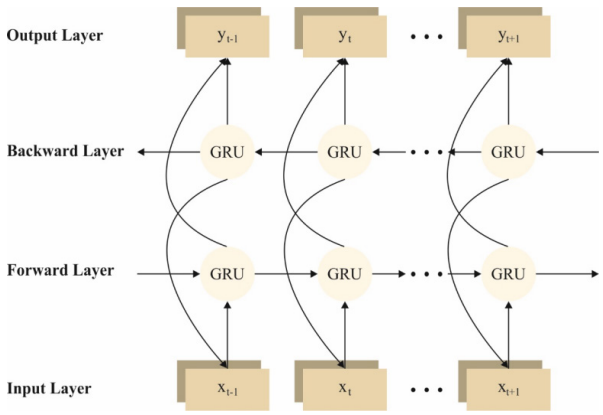

Figure 2: Architecture of BiGRU

Here, means a current iteration, represents the maximum iteration count, refers to the location of prey and indicates thehunterposition. aids in imitating the actions of attacking prey, and its value falls linearly from 2 to across iterations. and are chosen vectors at random from the range of and, correspondingly, that can certainly affect the exploration stage. If the global optimum is not recognized, the locations of prey in Eq. (14) are swapped by every leader's location because it is supposed that the leaders are next to the position of prey in the search area. Then, the locations of the remaining hunters will be upgraded by considering the position of leader with the below-mentioned Eq. (16):

$$\vec{X} = \frac{\sum_{i=1}^{N_l} \left(\vec{X}_{1,it}^{i} - \mu \cdot (2 \cdot \vec{r}_1 - 1) \cdot \left| \vec{r}_2 \cdot \vec{X}_{1,it}^{i} - \vec{X}_{it} \right| \right)}{N_l} \quad (16)$$

Here, mean a vector signifying the position of the leader between the group of leaders, and shows that a vector represents the location of a hunter. When the iteration rises, the group of hunters is upgraded near the leader's closet to the prey.

Exploration And Exploitation Phases

In the exploration stage, the hunters' main objective is to fully explore the hunting area and discover the most susceptible prey. The number of leaders is set as a greater amount. In exploitation, the major aim is to firmly encircle weak prey and add other predators to the ring. The group of leaders is decreased from to one and only leader by utilizing an exponential function utilizing Eq. 4. Which means the number of hunters. DHL has a robust exploitation stage and the exponential function used is below the given formula.

$$N_l = N_h \cdot \exp\left(\frac{it \cdot \ln\left(\frac{1}{N_h} \right)}{\text{Max}_{it}} \right) \quad (17)$$

The fitness choice is a major feature in managing the efficiency of DHL methodology. The parameter choice comprises the encoded model to calculate the effectiveness of candidate outcomes. For this paper, the DHL approach supposes accuracy as the most important criterion to make the fitness function (FF).

$$Fitness = \max(P) \quad (18)$$

$$P = \frac{TP}{TP + FP} \quad (19)$$

Here, TP and FP illustrate the true and false positive ratio.

Performance Validation

In this section, the performance validation of the BSHDHL-DLDDC model is examined using on ISIC 2017 dataset https://

challenge.isic-archive.com/data/. The dataset contains 318 samples with 7 classes, are demonstrated in Table 1.

Figure 3 displays the classifier outcomes of the BSHDHL-DLDDC model on the test dataset. Figures. 3a-3b exhibitions the confusion matrices with precise identification and classification of all class labels on a 70:30 TRASE/TESSE. Figure 3c presents the PR analysis, signifying maximum performance over all 7 classes. Eventually, Figure 3d describes the ROC analysis, displaying ability results with high ROC values for distinct 7 classes.

In Table 2 and Figure 4, the global detection outcomes of the BSHDHL-DLDDC algorithm are clearly displayed. The table values represented that the BSHDHL-DLDDC system is able to find the samples proficiently. On 70%TRASE, the BSHDHL-DLDDC technique attains average $accu_y$, $sens_y$, $spec_y$, $F1_{score}$ and MCC of 98.97, 95.11, 99.37, 95.93, and 95.42%. Moreover, on 30% TESSE, the BSHDHL-DLDDC methodology attains average $accu_y$, $sens_y$, $spec_y$, $F1_{score}$, and MCC of 98.81, 94.20, 99.28, 95.12, and 94.51%.

In Figure 5, the TRA (TRAAY) and validation (VLAAY) outcomes of the BSHDHL-DLDDC method are illustrated. The values are determined in a range of 0-30 epochs. The figure highlighted that the TRAAY and VLAAY values exhibit a tendency to increase which apprised the ability of the BSHDHL-DLDDC approach with better performance over a multitude of iterations. Moreover, the TRAAY and VLAAY remain firm above the epochs, which states slight overfitting and presents superior functioning of the BSHDHL-DLDDC system, securing constant anticipation on hidden samples.

In Figure 6, the TRA loss (TRALO) and VLA loss (VLALO) outcome of the BSHDHL-DLDDC algorithm is displayed. The loss values are computed over an interval of 0-30 epochs. It is depicted that the TRALO and VLALO values interpret a tendency to decrease, which reported the ability of the BSHDHL-DLDDC approach to compensate for a concession between data fitting and generalization. The consecutive dilution in loss values further assurances the better performance of the BSHDHL-DLDDC system and tunes the prediction results over time.

In Table 3, the overall comparison study of the BSHDHL-DLDDC methodology is precisely revealed Albakri, A. and

Table 1: Details of dataset

Class Labels	*No. of Samples*
"Angioma"	21
"Nevus"	46
"Lentigo NOS"	41
"Solar Lentigo"	68
"Melanoma"	51
"Seborrheic Keratosis"	54
"BCC"	37
Total count of Samples	318

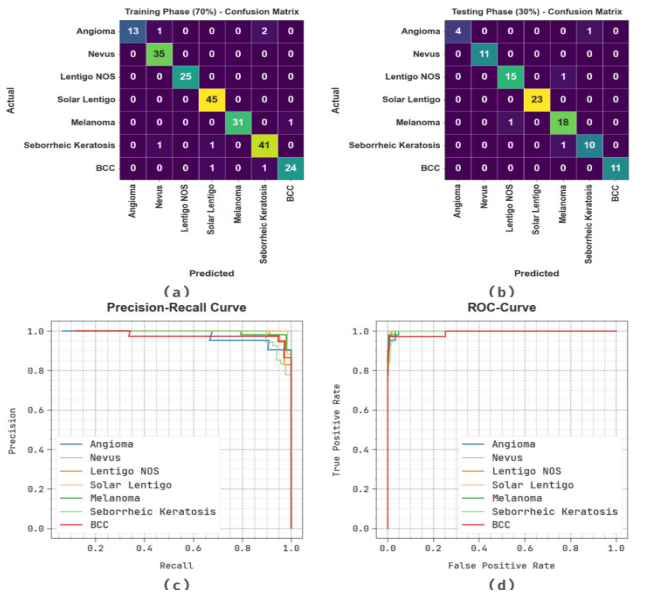

Figure 3: (a-b) Confusion matrices of 70:30 TRASE/TESSE and (c-d) PR and ROC analysis

Table 2: Overall detection of BSHDHL-DLDDC technique with 70:30 TRASE/TESSE

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	Fl_{Score}	*MCC*
TRASE (70%)					
Angioma	98.65	81.25	100.00	89.66	89.49
Nevus	99.10	100.00	98.93	97.22	96.74
Lentigo NOS	100.00	100.00	100.00	100.00	100.00
Solar Lentigo	99.10	100.00	98.87	97.83	97.29
Melanoma	99.55	96.88	100.00	98.41	98.17
Seborrheic Keratosis	97.75	95.35	98.32	94.25	92.86
BCC	98.65	92.31	99.49	94.12	93.38
Average	98.97	95.11	99.37	95.93	95.42
TESSE (30%)					
Angioma	98.96	80.00	100.00	88.89	88.96
Nevus	100.00	100.00	100.00	100.00	100.00
Lentigo NOS	97.92	93.75	98.75	93.75	92.50
Solar Lentigo	100.00	100.00	100.00	100.00	100.00
Melanoma	96.88	94.74	97.40	92.31	90.40
Seborrheic Keratosis	97.92	90.91	98.82	90.91	89.73
BCC	100.00	100.00	100.00	100.00	100.00
Average	98.81	94.20	99.28	95.12	94.51

Alqahtani, Y.M., 2023. Figure 7 reports the inquisition of the BSHDHL-DLDDC technique. The results expressed that the VGG19 model has shown unavailing detection results with the least of 91.34%. In the meantime, the DBN and YOLO-GC algorithms have presented somewhat higher performances with of 94.30% and 94.37%. Also, the ResNet, CDNN, and

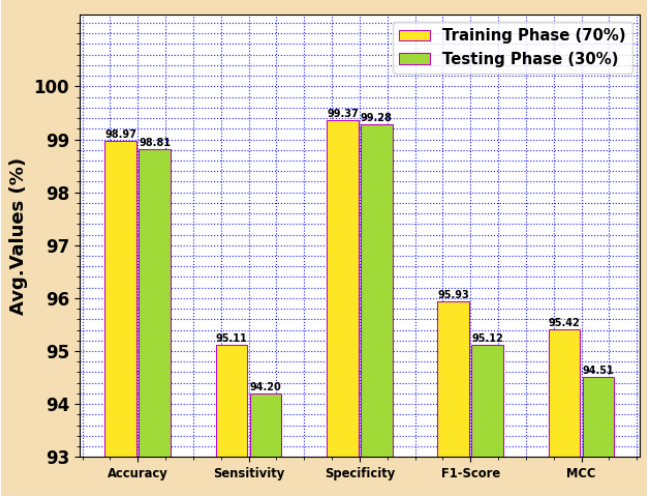

Figure 4: Average of BSHDHL-DLDDC technique with 70:30 TRASE/TESSE

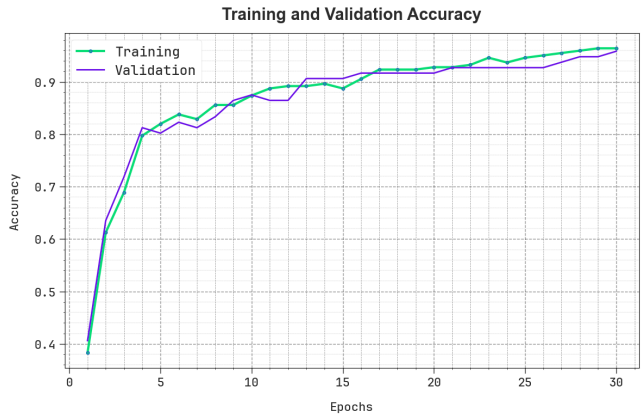

Figure 5: $Accu_y$ curve of the BSHDHL-DLDDC technique

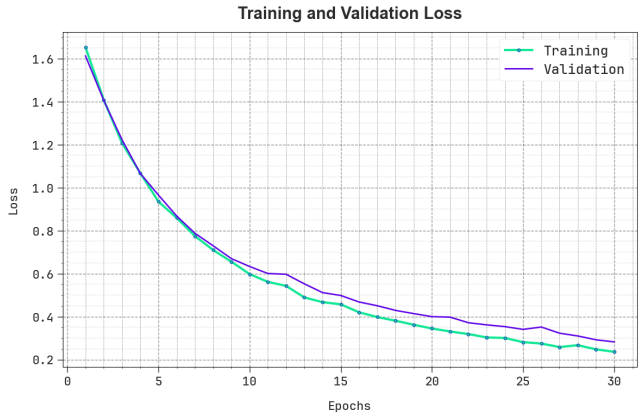

Figure 6: Loss curve of the BSHDHL – DLDDC technique

BSHS-EODL models have proficient reasonable outcomes with of 96.31%, 95.42%, and 98.62%. Lastly, the BSHDHL-DLDDC technique establishes outstanding performance with increased of 98.97%.

Figure 8 evaluates the comparative and outcomes of the BSHDHL-DLDDC technique. The results described that

Table 3 Comparative study of BSHDHL-DLDDC technique with other existing classifiers

Methods	$Accu_y$	$Sens_y$	$Spec_y$
BSHDHL-DLDDC	98.97	95.11	99.37
BSHS-EODL	98.62	93.12	99.25
DBN Algorithm	94.30	91.54	91.12
YOLO-GC Model	94.37	89.43	90.90
ResNet Methodology	96.31	90.58	91.18
VGG19 Model	91.34	90.31	93.84
CDNN Classifier	95.42	91.33	92.89

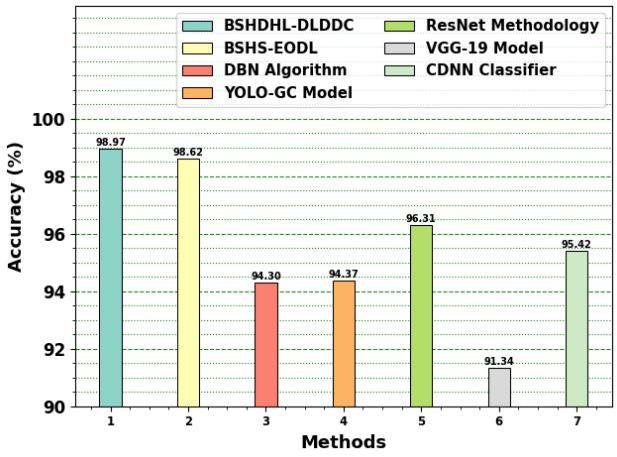

Figure 7: $Accu_y$ analysis of BSHDHL-DLDDC technique with other existing classifiers

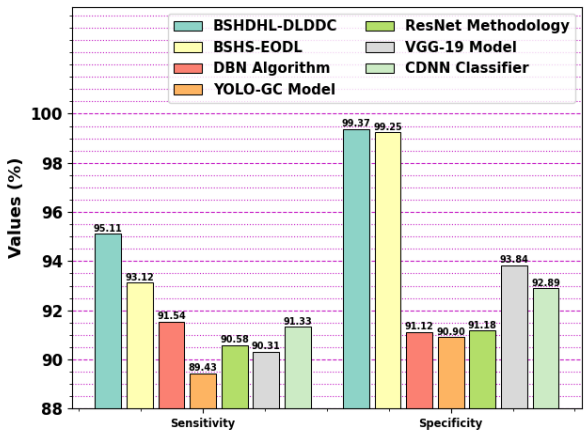

Figure 8: $Sens_y$ and $spec_y$ outcomes of BSHDHL-DLDDC technique with other existing classifiers

the BSHDHL-DLDDC system attained better performance. According to, the BSHDHL-DLDDC algorithm provides higher

of 95.11% while the BSHS-EODL, DBN, YOLO-GC, ResNet, VGG19, and CDNN methods offer inferior of 93.12, 91.54, 89.43, 90.58, 90.31, and 91.33%, respectively. Additionally, derived from, the BSHDHL-DLDDC model advances higher of 99.37% while the BSHS-EODL, DBN, YOLO-GC, ResNet, VGG19, and CDNN techniques achieve a minimum of 99.25, 91.12, 90.90, 91.18, 93.84%, and 92.89%, correspondingly.

Results

The study presents the design and development of the BSHDHL-DLDDC model, which combines deep learning and blockchain technologies to enhance disease diagnosis using medical images. Key results include:

Noise Reduction

The adaptive bilateral filtering (ABF) method effectively reduces noise in medical images while preserving critical edges and details.

Feature Extraction

The enhanced CapsNet model captures intricate spatial relationships in the images, significantly improving diagnostic precision.

Disease Classification

The BiGRU classifier successfully detects and classifies diseases.

Optimization

The dynamic hawk learning (DHL) algorithm fine-tunes the parameters of the BiGRU classifier, further enhancing classification performance.

Secure Data Management

The integration of blockchain technology ensures secure, decentralized, and tamper-proof storage of medical records, enabling secure data sharing without compromising patient privacy.

Comparison Studies: Simulation results demonstrate the superior performance of the BSHDHL-DLDDC model compared to existing methods, indicating its reliability and efficacy in medical image analysis.

Discussions

The BSHDHL-DLDDC model represents a significant advancement in medical image-based disease diagnosis, offering a robust, secure, and precise solution.

The integration of blockchain addresses critical challenges in healthcare, such as secure data sharing and privacy preservation, while simultaneously providing decentralized and immutable record storage.

The ABF method proves instrumental in pre-processing medical images, highlighting its role in improving downstream feature extraction and classification tasks.

The improved CapsNet model and BiGRU classifier leverage deep learning to achieve high accuracy in disease detection and classification, emphasizing their suitability for medical applications.

The application of the DHL algorithm in parameter optimization underscores the importance of advanced optimization techniques in enhancing model performance.

Comparative analysis with existing approaches underscores the potential of BSHDHL-DLDDC in real-world healthcare scenarios, offering higher accuracy and reliability.

Future studies could explore the scalability of the model across diverse datasets, including rare or complex disease categories, and assess its integration into existing healthcare workflows.

In conclusion, the BSHDHL-DLDDC model paves the way for next-generation diagnostic tools, combining the power of deep learning and blockchain to address contemporary challenges in medical image analysis and secure healthcare data management.

Conclusion

In this manuscript, we focus on the design and development of the BSHDHL-DLDDC model. The main goal of the BSHDHL-DLDDC method is to utilize deep learning techniques for accurate disease diagnosis from medical images.

To accomplish this, the integration of blockchain (BC) technology ensures decentralized, tamper-proof storage of medical records, allowing secure sharing between healthcare providers while retaining patient privacy.

Primarily, the BSHDHL-DLDDC technique applies an adaptive bilateral filtering (ABF) approach to effectively reduce noise while preserving important edges and details in medical images.

For the feature extractor process, the improved CapsNet model can be employed, capturing intricate spatial relationships within the images to enhance diagnostic precision.

In addition, the BiGRU classifier is performed to detect and classify diseases. To improve the classification performance of the BiGRU classifier, the parameter tuning process is performed through the Dynamic Hunting Leadership (DHL) algorithm.

A wide range of simulation studies is carried out to ensure the effectiveness of the BSHDHL-DLDDC technique. A comparison outcome highlighted the promising results of the BSHDHL-DLDDC approach over other existing methods.

References

Adegboye, O. R., Feda, A. K., Ojekemi, O. S., Agyekum, E. B., Elattar, E. E., & Kamel, S. (2024). Refinement of dynamic hunting leadership algorithm for enhanced numerical optimization. IEEE Access.

Albakri, A., & Alqahtani, Y. M. (2023). Internet of medical things with a blockchain-assisted smart healthcare system using metaheuristics with a deep learning model. Applied

Sciences, 13(10), 6108.

Anand, R., Kareem, S. F., Mubeen, R. M. A., Ramesh, S., & Vignesh, B. (2021, October). Analysis of heart risk detection in machine learning using blockchain. In 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC) (pp. 685–689). IEEE.

Bodkhe, U., Bhattacharya, P., Tanwar, S., Tyagi, S., Kumar, N., & Obaidat, M. (2019). Blohost: Blockchain-enabled smart tourism and hospitality management. In Proceedings of the International Conference on Computing, Information and Telecommunication Systems, Beijing, China (pp. 1–5).

Chatterjee, S., Bhattacharya, P., & De, D. (2024). LightDew: Lightweight blockchain-assisted dew computing framework for smart assisted living. IEEE Transactions on Consumer Electronics.

Gajndran, S., Muthusamy, R., Ravi, K., Chandraumakantham, O., & Marappan, S. (2024). Elliptic crypt with secured blockchain-assisted federated Q-learning framework for smart healthcare. IEEE Access.

Govindaram, A., & Jegatheesan, A. (2024). Enhancing industrial IoT security: Utilizing blockchain-assisted deep federated learning for collaborative intrusion detection. Journal of Electrical Systems, 20(2s), 1345–1363.

Healthcare Engineering, J. O. (2023). Retracted: SmartMedChain: A blockchain-based privacy-preserving smart healthcare framework.

Huang.H, P., Zhu, F., Xiao, X., Sun, Q., & Huang, Q. (2020). A blockchain-based scheme for privacy-preserving and secure sharing of medical data. Computers & Security, 99, 102010.

ISIC Archive. (n.d.). Challenge data. Retrieved from https://challenge.isic-archive.com/data/.

Li, C.-Y., Chen, X.-B., Chen, Y.-L., Hou, Y.-Y., & Li, J. (2019). A new lattice-based signature scheme in post-quantum blockchain network. IEEE Access, 7, 2026–2033.

Li, J., Li, D., & Zhang, X. (2023). A secure blockchain-assisted access control scheme for smart healthcare system in fog computing. IEEE Internet of Things Journal, 10(18), 15980–15989.

Lobo, V. B., Analin, J., Laban, R. M., & More, S. S. (2020, March). Convergence of blockchain and artificial intelligence to decentralize healthcare systems. In 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC) (pp. 925–931). IEEE.

Mao, R., Lee, J. E., & Edwards, M. C. (2024). A novel stacked hybrid autoencoder for imputing LISA data gaps. arXiv preprint arXiv:2410.05571.

Mistry.I, S., Tanwar, S., Tyagi, S., & Kumar, N. (2020). Blockchain for 5G-enabled IoT for industrial automation: A systematic review, solutions, and challenges. Mechanical Systems and Signal Processing, 135, 1–21.

Mohammed, M. A., Lakhan, A., Zebari, D. A., Abd Ghani, M. K., Marhoon, H. A., Abdulkareem, K. H., Nedoma, J., & Martinek, R. (2024). Securing healthcare data in industrial cyber-physical systems using combining deep learning and blockchain technology. Engineering Applications of Artificial Intelligence, 129, 107612.

Nouman, A., & Muneer, S. (2022). A systematic literature review on heart disease prediction using blockchain and machine learning techniques. International Journal of Computational and Innovative Sciences, 1(4), 1–6.

Nyemeesha, V., & Kavitha, M. (2025). Skin lesion classification using deep learning methods. Fusion: Practice and Applications, 17(1), 124–134.

Raju, K., Ramshankar, N., Shathik, J. A., & Lavanya, R. (2023). Blockchain-assisted cloud security and privacy preservation using hybridized encryption and deep learning mechanism in IoT-healthcare application. Journal of Grid Computing, 21(3), 45.

Shamshad, S., Minahil, K., Mahmood, K., Kumari, S., & Chen, C.-M. (2020). A secure blockchain-based e-health records storage and sharing scheme. Journal of Information Security and Applications, 55, 102590.

Tanwar, S., Parekh, K., & Evans, R. (2020). Blockchain-based electronic healthcare record system for healthcare 4.0 applications. Journal of Information Security and Applications, 50, 102407.

Wang, B., Wang, L., Xu, W., Ren, H., & Cheng, W. (2024). EEG-based motor imagery classification via multi-scale convolutional network and improved capsule network. Multimedia Tools and Applications.

Yu, H., He, F., & Pan, Y. (2020). A scalable region-based level set method using adaptive bilateral filter for noisy image segmentation. Multimedia Tools and Applications, 79, 5743–5765.