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A Blockchain and Hybrid Deep Learning for Secure and Efficient Healthcare Data Transmission and Management

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Abstract: The tremendous growth in technology has laid the foundations for more efficient solutions in the healthcare field, aiming to optimize security and scalability while improving patient care. This abstract presents an advanced methodology, leveraging hybrid deep learning techniques and blockchain (BC) technology to revolutionize healthcare system. BC technology provides a transparent and decentralized framework, which allows secured data sharing, storage, and access control. By incorporating BC into healthcare systems, interoperability, data integrity, and privacy can be ensured while disregarding the reliance on central authority. In combination with BC, hybrid DL methods provide powerful abilities for decision making and data analysis in healthcare. Integrating the strengths of deep learning (DL) techniques with classical machine learning methodologies, hybrid DL allows efficient and accurate processing of complicated healthcare data, such as sensor data, medical records, and images. This study presents a Blockchain with Deep Learning Assisted Data Transmission and Classification (BDC-DTC) technique in the healthcare sector. The presented BDC-DTC technique involves the design of image encryption with BC technology for achieving security in the healthcare sector. Initially, Elgamal encryption approach is used to encrypt the medical images which are then stored securely using BC technology. Next, the disease detection process is carried out using multi-faceted approach namely residual network (ResNet18) feature extractor, weIghted meaNoFvectOrs (INFO) based hyperparameter selection, and backpropagation neural network (BPNN) based classification. The simulation results of the BDC-DTC method can be studied using medical image database. The experimental outcomes specified that the BDC-DTC method gains superior performance over other models in terms of distinct measures.

Keywords: blockchain technology; deep learning; disease detection; healthcare data security; medical image encryption

1 INTRODUCTION

With arrival of 5G, Inter of Things (IoT), and Artificial Intelligence (AI), smart medicines have arisen as a securing application in present scenario [1]. Medical imageries are gradually forwarded on an open network as an outcome of spreads in tele-medicine in remote disease recognition and analysis. Doctors and patients nowadays have access to rapid medicinal analyses because of the steady combination of communication, computer, and multi-media technology in current medicine [2]. Patients who adore the ease of digital medicines have profited from these advanced technologies and enlarged the precision of medicinal analyses. Medical image diagnosis and storage are gradually causing the cloud, which is very essential for real remote analysis and resource sharing [3]. Therapeutic and diagnostic processes are made simpler by medicinal imaging tools. Maintaining the medical imagery while holding its consistency is crucial. A prohibited operator can modify medicinal imageries [4]. As a result of the data alteration in the image, disease analysis will be improper. As an outcome, a dependable and sturdy model for securely forwarding delicate health caution over public networks is needed. For this reason, before conveying information to a cloud server, we should initially encode it so that no one can be able to read it, not even the cloud server [5]. Traditional crypto-systems such as AES and DES are improper for rapid image encryption because they want a huge extent of computation power and a longer period to finish. Numerous encryption techniques were proposed to meet the principles of privacy, safety, and effective computation [6]. In the context of healthcare, blockchain (BC) technology has the latency in delivering crucial challenges associated with safety, data privacy, and interoperability [7]. Electronic health records (EHR), medical imaging data, and other delicate health data can be steadily kept and united between healthcare providers while certifying patient consent and data ownership. Furthermore, BC's distributed nature removes the necessity for intermediaries, decreasing costs, and improving data availability with sustainable development goals (SDG) [8]. While BC technology provides a strong foundation for healthcare methods, its latency can be enlarged further by integrating it with deep learning (DL) methods. DL is a sub-set of AI, which permits the analysis and removal of compound patterns and visions from larger-scale healthcare data [9]. Traditional ML methods frequently fight with the intrinsic complexity and heterogeneity of healthcare information, restraining their efficiency. On the other hand, DL techniques namely RNN and CNN, shine at identifying patterns in unstructured information such as natural language, sensor data, and medical images [10]. The proposed Blockchain with Deep Learning Assisted Data Transmission and Classification (BDC-DTC) methodology is designed to handle various types of medical image data effectively, showcasing robustness against different modalities and levels of image quality. The methodology employs ElGamal encryption with elliptic curve cryptography (ECC) to securely encrypt medical images before storage on the blockchain, ensuring strong security features and efficient handling of images of various sizes and qualities. Blockchain technology provides a decentralized and immutable ledger for storing these encrypted images, maintaining data integrity and preventing unauthorized access and tampering, regardless of the image modality or quality.

2 LITERATURE REVIEW

The authors [11] presented a new technique named DL and BC-enabled Secure Data Sharing. Mainly, DL methods are used to progress an effectual Intrusion Detection System (IDS). The projected RENS (intrusion recognition and identification) unites VariationalAutoEncoder (AE) with Attention-based Bi-LSTM for attack recognition and feature extraction. Furthermore, normal samples recognized by RENS were used in a BC-based access control device. In [12], an IoMT with BC-based smart healthcare model is projected by employing encryption with an optimal DL (BSHS-EODL) technique. Firstly, the IoMT devices permit collection of data procedures, and the collected imageries were kept in BC for safety purposes. Next, image encryption was used for data encryption. Lastly, the BSHS-EODL system executes illness analysis including Bayesian optimizer (BO) based hyperparameter tuning, SqueezeNet, and voting extreme learning machine (VELM). In [13] a new BC is projected with DL-aided safe medicinal data transmission and diagnoses (BDL-SMDTD) technique. This approach includes dissimilar phases of processes like encryption, BC, image acquisition, and diagnostic procedure. Chiefly, moth flame optimizer (MFO) with elliptic curve cryptography (ECC), named MFO-ECC system is employed for the image encryption procedure where the optimum keys of ECC were produced utilizing MFO technique. Also, BC technique was employed to keep the encoded imageries. Then, the analytic procedure includes Inception with ResNetV2-based feature extraction, histogram-based segmentation, and SVM-based identification. In [14] is presented BC-driven privacy-preserving; EHR diagnosis utilizing a sine cosine algorithm (SCA) with a DL method called BPEHR-SCADL model. This technique mainly projects an artificial fish swarm algorithm (AFSA) with a signcryption method to safely convey EHRs. Furthermore, the BPEHR-SCADL system utilizes BC technology. Furthermore, the SCA with a deep feedforward neural networks (DFFNNs) approach is used for the classification procedure. Besides, the SCA is employed to alter the bias and weight values of the DFFNN method. In [15] BC aided IoT Healthcare System is presented using Ant Lion Optimizer with Hybrid DL (BHS-ALOHDL) system. This method executes ALO based feature sub-set selection (ALO-FSS) technique to yield a sequence of feature vectors. The HDL system unites CNN features and LSTM method for intrusion recognition. Finally, the flower pollination algorithm (FPA) is developed for the parameter adjustment of the HDL system. The authors [16] constructed a remote intellectual healthcare method based on BC. This model covers dual layers such as Sensing Communication Layer (SenCom-Layer) and the BC-Layer. In SenCom-Layer, an Energy-aware Whittle Index-based Algorithm (EWIA) technique is projected. In BC-Layer, since both the two values of block nodes and the method, an Energy-efficient DPoS-based cooperative game is presented. In [17], a safe outsourcing scheme utilizing a DL structure is projected. Originally, the medical data was gathered from normal datasets, and it is encoded by employing the Optimal Key-based Hybrid Elliptic Curve Cryptography with Fully Homomorphic Encryption (OK-HECCFHE), while the optimum key has been produced utilizing Hybrid Polar Bear-Ageist Spider Monkey Optimizer (HPB-ASMO) model. Next, the optimum key was used, and then the medical data forecast was completed through the Optimized DNN with the GRU networks. This study presents a Blockchain with Deep Learning Assisted Data Transmission and Classification (BDC-DTC) technique in the healthcare sector. The presented BDC-DTC technique involves the design of image encryption with BC technology for achieving security in the healthcare sector. Initially, Elgamal encryption approach is used to encrypt the medical images which are then stored securely using BC technology. Next, the disease detection process is carried out using multi-faceted approach namely residual network (ResNet18) feature extractor, weIghtedmeaNoFvectOrs (INFO) based hyperparameter selection, and backpropagation neural network (BPNN) based classification. The simulation results of the BDC-DTC technique can be studied using medical image database.

3 THE PROPOSED METHOD

In this study, we have presented a BDC-DTC technique in the healthcare sector. The presented BDC-DTC technique involves the design of image encryption with BC technology for achieving security in the healthcare sector. Fig. 1 illustrates the working flow of BDC-DTC method.

Encryption Approach.

The proposed BDC-DTC methodology utilizes a combination of ElGamal encryption and elliptic curve cryptography (ECC) to ensure the secure transfer of medical images. ElGamal encryption, a public-key cryptosystem, is known for its robustness and security, relying on the difficulty of solving discrete logarithm problems for encryption and decryption processes. By incorporating ECC, the methodology enhances security further while maintaining computational efficiency. ECC is favored for its ability to provide strong security with shorter key lengths compared to other encryption methods like RSA, making it particularly suitable for environments with limited processing power and storage, such as in medical imaging systems. This dual approach ensures that medical images are encrypted before transmission, protecting patient data from unauthorized access and ensuring compliance with stringent data protection regulations. The selection of standard medical images for assessing the proposed BDC-DTC methodology involved curating a diverse dataset that included various types of medical imaging modalities such as X-rays, MRIs, CT scans, and ultrasound images. This diversity ensured that the methodology's performance could be evaluated across different imaging techniques, each with its unique characteristics and challenges. The chosen images were sourced from reputable medical imaging databases and repositories, ensuring they met the quality standards typically required for clinical diagnosis and research. This comprehensive selection process was designed to test the algorithm's robustness and generalizability across different types of medical images. Initially, the medical image encryption technique is performed by the ElGamal Encryption method. The ECC-based ElGamal encryption uses different parameters and steps [18]. The additive homomorphic technique is expressed as follows:

$$E\left(m_1\right)+E\left(m_2\right)=E\left(m_1+m_2\right) \tag{1}$$

In Eq. (1), the "+" and "E" are the additive homomorphic and the public key. The additive homomorphic encryption is considered in ECC. According to the elliptic curve's (ECs) algebraic infrastructure on finite field, ECC-based ElGamal is illustrated. The finite domain was split into 2 binary and prime domains 2_n. Here, ECs over the prime domain were examined.

$$y^2 = x^3 + ax + b \tag{2}$$

where $E_r(a, b)$ is the resultant curve, r is the modulus, and a and b are the new coefficients. The x values range from 0 to r.

BC Technology.

BC is used as a decentralized data storage technique to generate the ledger that avoids third-party access and allows access to the users for the encrypted information [19]. BC is an immutable decentralized data for that new timestamp transaction was added to hash-chain of block. The BC protocol determines that various copies of these blocks are created and retained in a decentralized manner. The significant part of these protocols decide that network of participants recognises that miner, and finds consensus on present state of BC. BC has public, private, permissioned, and permission-less. Proof of Stake (PoS) and Proof of Work (PoW) are the two major techniques in BCs. Once the task is completed, a new transaction is combined with the BC. Some miners perform calculations to establish their credibility as leaders. It solves the puzzle to arbitrarily map data size to set the size.

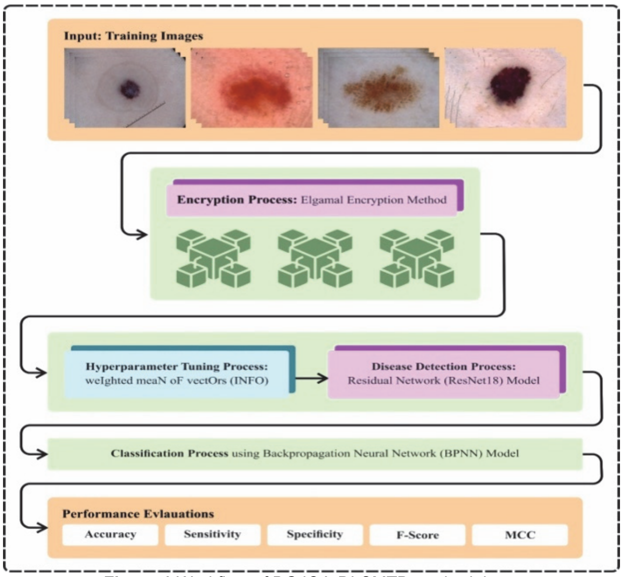

Figure 1 Workflow of BGJOA-DLSMTD methodology

Blockchain (BC) technology contributes to storing encrypted medical images primarily by providing a decentralized and immutable ledger for data storage and access control. Each medical image, encrypted for privacy and security, can be stored as a transaction on the blockchain network. This decentralization ensures that the data is not stored in a single centralized location, reducing the risk of data breaches or unauthorized access. Additionally, the immutability of the blockchain ensures that once a medical image is stored, it cannot be altered or tampered with, maintaining the integrity of the data. Access control mechanisms, such as smart contracts, can be implemented on the blockchain to manage permissions for viewing or sharing medical images, further enhancing security. In general, a leader is designated from the above two techniques. In PoW, different miners try to resolve the puzzle and transfer it to the group proof. Then, another miner confirms that the work is accurately completed. Then, it chooses miner as a leader. Due to the subsequent properties, the hash function was effective:

- It generates an outcome of set length notwithstanding the input length.
- It irreversibly represents that attaining an input in the outcome is not possible.
- It is deterministic which signifies that it makes a corresponding outcome to the given input.
- The computation of hash is quicker with less overhead.
- Some small perturbation to the original input generates a new output.

Disease Detection

Next, the disease detection process is carried out using multi-faceted approach namely ResNet18 feature extractor, INFO-based hyperparameter selection, and BPNN-based classification.

ResNet.

CNN is a deep learning (DL) algorithm mainly applied for computer vision and image recognition tasks [20]. The convolution operation, which acts as a building block of a CNN, extracts features through the filter (a.k.a. feature detector convolution or kernel) to the input dataset. The primary step of CNN entails the traversal of convolution filter across the input images, leading to the generation of feature map through summation and component-wise multiplication between the filter and the input image. It can extract more sophisticated features by integrating multiple filters within the convolutional layer. The function is widely used for the convolution operation and the resulting feature map. The integration of pooling layer is aimed at reducing the network parameter and spatial dimension of feature map while maintaining the key features. After the sequence of pooling and convolutional layers, the resultant feature map is transformed into 1D vector and consequently traverses the full connection layer. The output layer defines the suitable activation function. The CNN utilizes the backpropagation model to repeatedly update weights and biases of the networks during the training process, which facilitates gradual attainment of feature representation from the input dataset. The application of hierarchical structure and convolution operation in CNN allows effective learning and feature extraction from the image, thereby improving analysis and image processing abilities. The deep residual network (DRN) is a DNN model used for the DL and image classification tasks. Classical deep neural network encounters problems like exploding and vanishing gradient problems, which impede successful training with increasing depth of network. Furthermore, the increasing amount of computational complexity and parameters worsen these problems. The integration of residual connection in DRN efficiently addresses these challenges of deep network training, thereby facilitating optimization and making it possible to implement more complex network architecture. ResNet presents residual blocks, including residual and identity maps.

$$y = F\left(x, \{W_i\}\right) + x \tag{3}$$

In Eq. (3), y indicates the output of residual block, x denotes the input, F refers to the residual mapping, and $\{W_i\}$ refers to the learnable parameter in the residual maps (convolutional kernel weight). The novelty of ResNet lies in the residual learning, a concept that has considerably improved DNN architecture. In the deep CNN (DCNN), input dataset is processed by multiple layers to attain the output. It enables the output of main pathway and direct skipping of multiple layers integrated with the main pathway of network layer in ResNet. The ResNet addresses the problems of explosion and vanishing gradient effectively in DNNs, which enables to improvement of its depth for better performance. In this study, the ResNet-18 architecture is used based on the available computational resources and practical requirements. It includes 18 layers (the pooling layer and activation function). Due to its residual architecture, ResNet18 facilitate direct BP of gradients to initial layer, which mitigates the gradient vanishing problems. Furthermore, the present model showcases a reduced scale, requiring less storage and capacity computational resources than the deep model within the ResNet series, namely ResNet50 and ResNet101; nonetheless, it shows improved performance, enhanced training and inference speed.

Classification Process.

BPNN is a FFNN with backpropagation of errors [21-24]. The BPNN has the hidden layer (HL), input, and output layers. The number of neurons and layers in the HL is defined by the dimension of the input and output vectors. Fig. 2 represents the architecture of BPNN. Generally, BPNN is set up with a single HL. BPNN can memorize and learn input-output mapping models without requiring prior mathematical formula. During the network learning process, the signal includes forward and backward propagation. If the actual output of output layer varies from the expected value, the error is propagated backwards. The learning rule uses the steepest descent algorithm, which continually updates the weight and bias of the NN through iterative operation to reduce the network error.

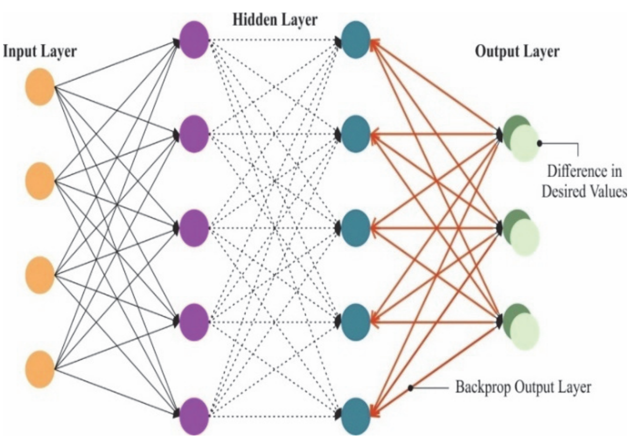

Figure 2 Architecture of BPNN

4 RESULT ANALYSIS AND DISCUSSION

The performance analysis of the BDC-DTC method is tested using skin lesion dataset [25]. It includes 318 samples with 7 classes as shown in Tab. 1. Fig. 3 defines the sample images.

Table 1 Details on database

Labels	Class	No. of Images
C0	Angioma	21
C1	Nevus	46
C2	Lentigo NOS	41
C3	Solar Lentigo	68
C4	Melanoma	51
C5	Seborrheic Keratosis	54
C6	BCC	37
Total No. of Images		318

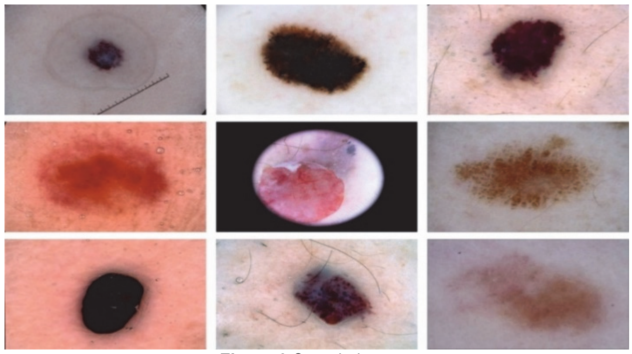

Figure 3 Sample images

Fig. 4 determines the confusion matrices generated by the BDC-DTC method under 80:20 and 70:30 of TRAS/TESS. The outcome shows that the BDC-DTC algorithm has effective detection and recognition of all six classes accurately.

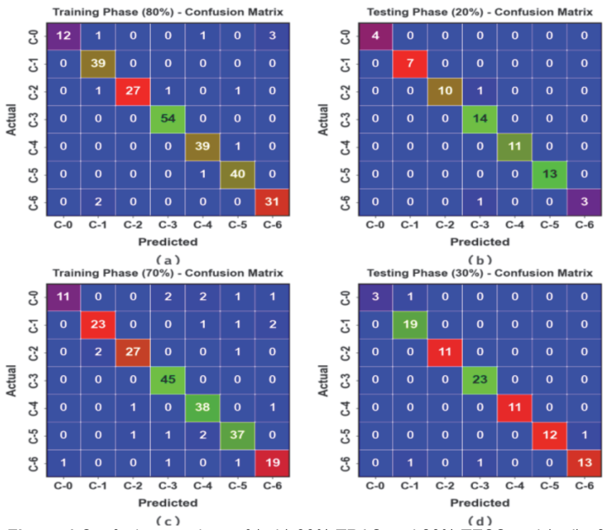

Figure 4 Confusion matrices of (a-b) 80% TRAS and 20% TESS and (c-d) 70% TRAS and 30% TESS

In Tab. 2 and Fig. 5, the detection outcomes of the BDC-DTC technique are reported with 80% TRAS and 20% TESS. The results showed that the BDC-DTC technique effectually recognizes the samples. With 80% TRAS, the BDC-DTC technique offers average $accu_y$, $sens_y$, $spec_y$, F_{score} and MCC of 98.65%, 92.80%, 99.20%, 93.85%, and 93.33%, correspondingly. Also, with 20% TESS, the BDC-DTC technique offers average $accu_y$, $sens_y$, $spec_y$, F_{score} and MCC of 99.11%, 95.13%, 99.43%, 96.33%, and 96.00%, correspondingly.

Table 2 Detection outcome of BDC-DTC technique with 80% TRAS and 20% TESS

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}	MCC
TRAS (80%)					
C-0	98.03	70.59	100.00	82.76	83.14
C-1	98.43	100.00	98.14	95.12	94.35
C-2	98.82	90.00	100.00	94.74	94.24
C-3	99.61	100.00	99.50	99.08	98.84
C-4	98.82	97.50	99.07	96.30	95.60
C-5	98.82	97.56	99.06	96.39	95.69
C-6	98.03	93.94	98.64	92.54	91.42
Average	98.65	92.80	99.20	93.85	93.33
TESS (20%)					
C-0	100.00	100.00	100.00	100.00	100.00
C-1	100.00	100.00	100.00	100.00	100.00
C-2	98.44	90.91	100.00	95.24	94.46
C-3	96.88	100.00	96.00	93.33	91.65
C-4	100.00	100.00	100.00	100.00	100.00
C-5	100.00	100.00	100.00	100.00	100.00
C-6	98.44	75.00	100.00	85.71	85.89
Average	99.11	95.13	99.43	96.33	96.00

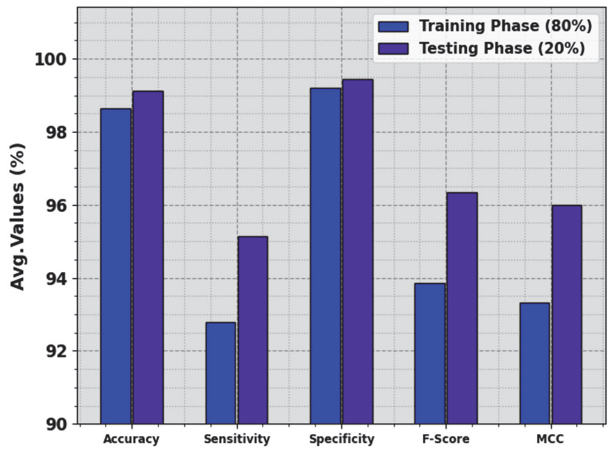

Figure 5 Average of BDC-DTC technique with 80% TRAS and 20% TESS

Table 3 Detection outcome of BDC-DTC technique with 70% TRAS and 30% TESS

Class Labels	$Accu_y$	$Sens_y$	$Spec_y$	F_{score}	MCC
TRAS (70%)					
C-0	96.85	64.71	99.51	75.86	75.52
C-1	97.30	85.19	98.97	88.46	87.02
C-2	97.75	90.00	98.96	91.53	90.24
C-3	98.20	100.00	97.74	95.74	94.74
C-4	96.85	95.00	97.25	91.57	89.72
C-5	96.40	90.24	97.79	90.24	88.03
C-6	96.85	86.36	98.00	84.44	82.72
Average	97.17	87.36	98.32	88.26	86.86
TESS (30%)					
C-0	98.96	75.00	100.00	85.71	86.14
C-1	97.92	100.00	97.40	95.00	93.88
C-2	100.00	100.00	100.00	100.00	100.00
C-3	98.96	100.00	98.63	97.87	97.22
C-4	100.00	100.00	100.00	100.00	100.00
C-5	98.96	92.31	100.00	96.00	95.50
C-6	96.88	86.67	98.77	89.66	87.89
Average	98.81	93.42	99.26	94.89	94.38

In Tab. 3 and Fig. 6, the detection outcomes of the BDC-DTC method are reported with 70% TRAS and 30% TESS. The outcomes exhibited that the BDC-DTC system effectively recognizes the samples. With 70% TRAS, the BDC-DTC technique provides average $accu_y$, $sens_y$, $spec_y$, F_{score} and MCC of 97.17%, 87.36%, 98.32%, 88.26%, and 86.86%, correspondingly. Also, with 30% TESS, the BDC-DTC approach provides average $accu_y$, $sens_y$, $spec_y$, F_{score} and MCC of 98.81%, 93.42%, 99.26%, 94.89%, and 94.38%, correspondingly.

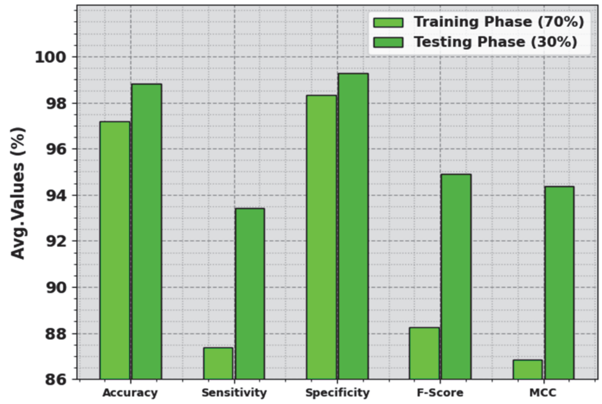

Figure 6 Average of BDC-DTC technique with 70% TRAS and 30% TESS

Table 4 Comparative analysis of BDC-DTC technique with recent models

Methods	$Accu_y$	$Sens_y$	$Spec_y$
BDC-DTC	99.11	95.13	99.43
BGJOA-DLSMTD	98.99	95.72	99.41
BSHS-EODL	98.51	92.98	99.11
DBN Algorithm	94.15	91.40	90.98
YOLO-GC	94.24	89.30	90.77
ResNet Model	96.19	90.44	91.03
VGG-19 Model	91.19	90.20	93.73
CDNN Model	95.29	91.19	92.77

The comparison studies of the BDC-DTC technique with recent models have appeared in Tab. 4 [12]. The comparative $accu_y$ results of the BDC-DTC technique are provided. Based on $accu_y$, the BDC-DTC technique gains increasing $accu_y$ of 99.11% while the BSHS-EODL, DBN, YOLO-GC, ResNet, VGG-19, and CNN models have obtained reducing $accu_y$ of 98.51%, 94.15%, 94.24%, 96.19%, 91.19%, and 95.29%, correspondingly.Thus, the BDC-DTC technique can be applied for enhanced detection process.

5 CONCLUSION

In this study, we have established a BDC-DTC method in the healthcare sector. The presented BDC-DTC technique involves the design of image encryption with BC technology for achieving security in the healthcare sector. Initially, Elgamal encryption approach is used to encrypt the medical images which are then stored securely using BC technology. Next, the disease detection process is carried out using multi-faceted approach namely ResNet18 feature extractor, INFO-based hyperparameter selection, and BPNN-based classification. The experimental results of the BDC-DTC technique can be studied using medical image database. The experimental outcomes stated that the BDC-DTC approach gains superior performance over other techniques under distinct measures.

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