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DeepRing: Convolution Neural Network based on Blockchain Technology

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ABSTRACT: ***Background:*** *This paper addresses specific challenges in predictive modeling, namely transparency issues, susceptibility to data manipulation, and fairness concerns. To overcome these obstacles, the study introduces DeepRing, approach that combines Convolutional Neural Networks (CNNs) and blockchain technology.* ***Objective:*** *DeepRing aims to enhance prediction integrity, data security, and fairness, thereby improving the ethical considerations, reliability, and accountability of predictive models.* ***Methods:*** *involves iterative training of a CNN model on five diverse datasets, including CIFAR-10, Fashion-MNIST, MNIST, CIFAR-100, and a Hands dataset. The CNN architecture incorporates Conv2D layers, MaxPooling2D layers, and Dense layers. Training metrics such as accuracy and sparse categorical cross-entropy loss are monitored, with the Adam optimizer employed. While achieving high accuracy on Plam (0.5300), MNIST (0.9978) and Fashion MNIST (0.9673), DeepRing exhibits moderate performance on CIFAR-10 (0.9296) and lower accuracy on CIFAR-100 (0.5973).* ***Results:*** *demonstrate the effectiveness of DeepRing in improving accuracy and enhancing model performance across various datasets. However, further development and validation are essential for successful model implementation, further development and validation are essential for successful model implementation.* ***Conclusions:*** *Introduces DeepRing as an innovative solution to address key challenges in predictive modeling, specifically focusing on transparency issues, susceptibility to data manipulation, and fairness concerns. By combining Convolutional Neural Networks (CNNs) with blockchain technology, DeepRing aims to elevate prediction integrity, enhance data security, and promote fairness, thereby contributing to the improvement of ethical considerations, reliability, and accountability in predictive modelling.*

KEYWORDS: *DeepRing; CNN; Blockchain technology; Fashion- MNIST; MNIST*

INTRODUCTION

The integration of deep learning with blockchain technology has witnessed significant advancements and found applications in various domains such as smart computing, fog computing, and the Internet of Things. Blockchain's decentralized and secure nature has made it useful for safeguarding sensitive data, influencing fields like science, image recognition, face search applications, emotion recognition, healthcare, and decision-making [1]. This section provides an overview of modern blockchain-based deep learning, offering insights into blockchain technology and deep learning models [2]. Deep learning involves convolutional neural networks (CNNs), a class of artificial neural networks primarily used for visual imagery analysis. CNNs were inspired by the visual perception process and are capable of extracting features from data using convolution structures. The effectiveness and efficiency of deep learning greatly depend on high-quality training data. However, centralized storage and processing of the training model present single points of failure and vulnerability to data changes [3]. Blockchain, as a decentralized technology, offers a solution to these issues, enhancing the reliability and security of deep learning models. By utilizing blockchain with deep learning, various benefits can be achieved, such as strengthening model security, facilitating model sharing, and automating decision-making. Blockchain's decentralized ledger ensures data integrity and tracks transactions, reducing the chances of data manipulation and fraud [4]. The integration of smart contracts within the blockchain is a pivotal aspect of this endeavor, as it aims to automate operations and eliminate the need for intermediaries, thus making the system more efficient and trustworthy [5]. The objective of this thesis is to design and evaluate a hybrid CNN model that leverages blockchain technology for the training of a biometric recognition system [6]. By capitalizing on the security features inherent to blockchain, the proposed architecture seeks to establish a robust and reliable model for biometric recognition [7]. This amalgamation bears the potential to revolutionize biometric security systems and various other domains that demand elevated data integrity and trust. The combination of deep learning and blockchain technology represents a compelling solution for ensuring the security and credibility of artificial intelligence (AI) systems, fostering collaboration, and laying a solid foundation for a spectrum of applications across diverse industries. The forthcoming sections of this work will delve into the methodology, data sources, model architecture, training processes, and performance evaluations that underpin the implementation and assessment of this innovative hybrid CNN model with blockchain technology for biometric recognition [8].

RELATED WORK

Several proposals from different researchers are discussed, each addressing specific applications of deep learning in conjunction with blockchain such as: [9], and others in 2019 It is advised that access to individual wallets be restricted via biometric encryption techniques. The CNN recognizes faces as a means of extracting biometric characteristics that aid in the primary link method to protecting personal data in the wallet via two layers, the first one is the classification layer while the second one is represented by biometric features. The outcomes are good, however when testing on pictures from the same training set as the CNN, the equal error-rate between erroneous acceptance and false rejection is insignificant. This proposal demonstrated the viability of using face encryption systems to secure access to private information stored in electronic wallets. The model also demonstrated deep facial recognition with a 99.3% accuracy rate.

Goel and Agarwal [10] 2019 introduced a deep neural network protected from external attacks using blockchain and encryption technologies. They also suggested a fresh approach to tamper with settings to enhance deep learning in blockchain technology. Kim and Cho [11] in 2019 presented CNN-LSTM, a hybrid model capable of extracting both temporal and geographical information for forecasting energy consumption in housing. The model successfully predicted electrical energy usage with high accuracy. X. Li and J. Li [12] 2019 proposed a directed loop graph network that combines CNN and LSTM to forecast the remaining usable life of machines. The model outperformed individual CNN and LSTM algorithms on the same dataset. Taha and Safauldeen [13] 2020 linked blockchain technology with LSTM-based neural networks to conduct secure diagnostics and predict successful trading signals for different blockchains. Their model achieved an accuracy of 95.85% in forecasting trading signals for insurance. Alam and Islam [14] 2022 presented a CNN-blockchain hybrid model to prevent malicious data transactions and malware injection in blockchain networks. Their proposed VGG-16 model achieved an accuracy of up to 95.3%. Chandra and Rajendran [15] in 2022 introduced a hybrid CNN-LSTM model for Bitcoin transactions, providing a reliable and safe distributed system for data replication. The model utilized Bitcoin and fast CNN to overcome the limitations of third-party transactions. Furthermore, Patel and Sanghvi [16] in 2022 proposed the BlockCrime CNN-based Xception model, incorporating blockchain technology to securely store crime scene locations and notify nearby law enforcement agencies. The Xception architecture outperformed traditional CNN architectures with an accuracy of 96.57%.methods, and the accuracy is 99.56%.

MATERIALS AND METHODS

Dataset

The work utilizes five datasets: CIFAR-10, Fashion-MNIST, MNIST, Plam and CIFAR-100. Consists of 60,000 low-resolution color images grouped into 10 classes. Fashion-MNIST comprises 60,000 grayscale images of fashion items categorized into 10 classes. MNIST contains 60,000 grayscale images of handwritten digits, and CIFAR-100 has 60,000 low-resolution color images split into 100 classes

Deep Learning Approaches

This section provides an overview of deep learning approaches and methods, highlighting their significance in the field of AI. Deep learning algorithms, such as artificial neural networks and CNNs, are continuously advancing machine learning capabilities, enabling computers to learn from data and make predictions based on experiences. These techniques aim to model the human brain's processes, creating and maintaining representations of the world for improved AI applications [17]. Deep learning proves to be particularly useful in various scenarios, often surpassing human expertise in specific tasks. Some of these situations include cases where human experts are unavailable, instances where human decision-making cannot be explained (e.g., medical decisions, speech recognition), and situations where solutions evolve over time (e.g., stock prediction, weather forecasting). Furthermore, deep learning is beneficial when solutions require adaptation based on specific cases, and when dealing with enormous problem sizes that exceed human reasoning capabilities [18]. To optimize deep learning algorithms and reduce training time, various methods can be employed. These techniques include backpropagation, stochastic gradient descent, learning rate decay, dropout, max-pooling, batch normalization, skip-gram, and transfer learning. Each of these methods contributes to improving the performance and robustness of deep learning models. The study also outlines popular deep learning frameworks, including recurrent neural networks (RNNs), deep belief networks (DBNs), deep neural networks (DNNs), and CNNs. Each framework specializes in solving specific problems, with CNNs, in particular, excelling in processing spatial or grid-like data, such as images or videos [19]. CNNs consist of multiple layers, including convolution, pooling, fully connected, and non-linearity layers as shown in figure1. The convolution layer applies filters to the input data, extracting features from the image. The pooling layer reduces the feature dimensionality and improves model robustness. The fully connected layer combines features from the convolutional layers, and the non-linearity layer introduces non-linear transformations to the output [20].

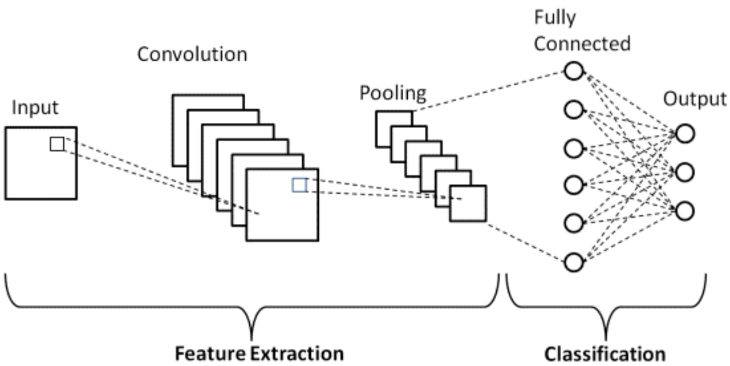

Figure 1. Typical Convolutional Neural Network Layer [20]

The Blockchain Technology

This section discusses the architecture and types of blockchain, highlighting its features and advantages. The blockchain is a distributed, tamper-aware, and fault-tolerant database that links blocks together using cryptographic hash functions. Each block contains a hash of the previous block's header, creating an immutable chain of records [21]. A blockchain consists of two main components: a distributed database and a network of nodes as shown in Figure 2. The database stores records in the form of transactions, bundled together to form blocks. Each block is linked to its predecessor by a hash, and the entire network of nodes maintains the database in a peer-to-peer fashion. Transactions are signed, making them secure and tamper-proof [22]. There are three types of blockchain: private, public, and consortium. Private blockchains are controlled by specific organizations and have limited access, while public blockchains are open to anyone and are fully decentralized. Consortium blockchains are semi-decentralized and involve multiple organizations collaborating on a network [23]. Some key features of blockchain technology include decentralization of consensus, blockchain immutability (tamper-evidence), security, and privacy. Blockchain ensures that transactions are agreed upon and verified through the consensus of network participants without a central authority. Transactions are recorded in an irreversible and tamper-evident manner, enhancing security. Smart contracts further enable automation and eliminate the need for intermediaries in contractual agreements [24]. Blockchain also offers advantages in various applications, including financial and non-financial use cases. These benefits include increased security, transparency, traceability, reduced costs, and improved efficiency [25].

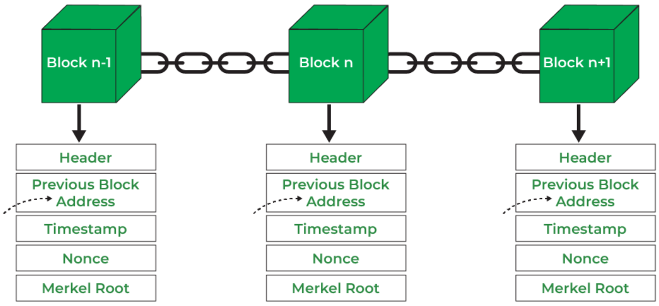

Figure 2. Blockchain architecture [25]

Proposed Combination of CNN and Blockchain

The DeepRing is a proposed model that combines the power of CNNs with the security and transparency offered by blockchain technology. The key idea behind DeepRing is to utilize blockchain as a tamper-evident and decentralized ledger to store the predictions made by CNN models. By storing prediction hashes on a blockchain, it becomes possible to verify the authenticity and integrity of the predictions, ensuring that they haven't been altered or manipulated. The work DeepRing as following in Figure 3.

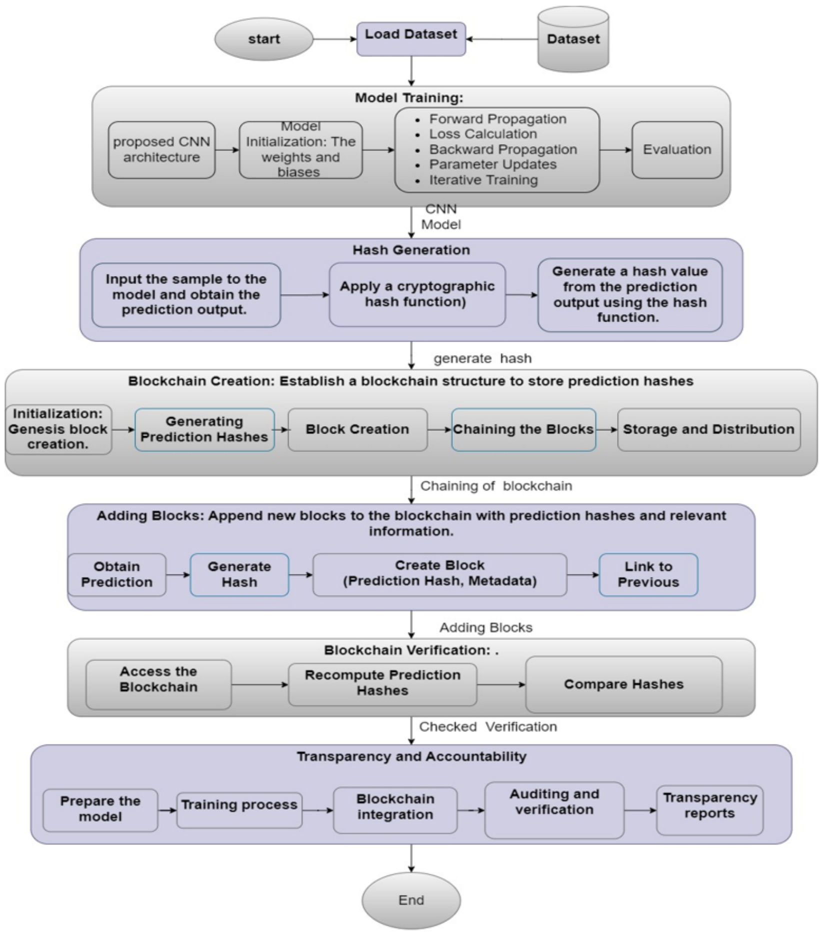

Figure 3. the block diagram of proposed work

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It is challenging for any one organization to change or falsify the recorded prediction hashes without being discovered since the blockchain is decentralized and dispersed. As a result, DeepRing combines CNNs and blockchain technology to enhance the reliability and integrity of deep learning models. By storing prediction hashes in a decentralized and dispersed blockchain, DeepRing prevents data manipulation, model bias, and security breaches. It offers transparency, accountability, and the ability to independently verify and audit model predictions, making it suitable for critical applications requiring fairness and trust. Although DeepRing is a conceptual suggestion, its implementation would require further study, development, and validation, considering factors like cryptographic hash functions, blockchain consensus processes, scalability, and system architecture.

RESULTS AND DISCUSSION

In this section presents the results and analysis of the proposed DeepRing by using, It begins with describing the experimental setup and evaluation metrics, followed by presenting the results and analyzing the findings. In this work used five datasets, CIFAR-10, Fashion-MNIST, MNIST, Hand, and CIFAR-100, as shown in Figure 2, the properties of each dataset: CIFAR-10 (60,000 images, 32x32 RGB, 10 classes), Fashion-MNIST (60,000 images, 28x28 grayscale, 10 classes), MNIST (70,000 images, 28x28 grayscale, 10 classes), CIFAR-100 (60,000 images, 32x32 RGB, 100 classes), and Hands dataset (11,076 images, 1600x1200 pixels, 190 subjects). The next step is to normalize the dataset that by scales down the pixel values of the images to a standardized range as shown in Figure 4.

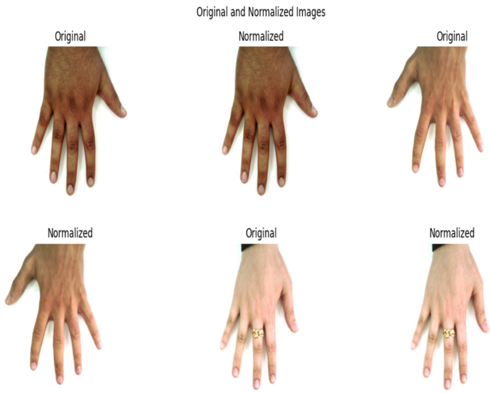

Figure 4. Normalized the Palm datasets

The training process involves several stages, starting with dataset preparation and the definition of the CNN model architecture. The CNN model includes Conv2D layers for feature extraction, followed by MaxPooling2D layers for downsampling. ReLU activation introduces non-linearity, and the Flatten layer converts the output into a 1D vector for processing by fully connected Dense layers. The first Dense layer with 256 units and ReLU activation generates the hash key, while the final Dense layer with num_classes units and softmax activation computes the hash.

The model is compiled using the Adam optimizer, sparse categorical cross-entropy loss, and accuracy as the evaluation metric. It is trained for 10 epochs on the training dataset. During training, the model updates its parameters to minimize the loss and improve accuracy. The training history is monitoring the loss and accuracy metrics, the model's performance is evaluated. The iterative training process allows the model to learn the dataset's patterns and improve its predictions as shown in Table 1 and Figure 4.

Table 1 and Figure 5 show the training results for different datasets (MNIST, Plam, Fashion-MNIST, CIFAR-10, and CIFAR-100) demonstrate the effectiveness of the CNN model. The loss consistently decreases with each epoch, indicating improved predictions and feature extraction capabilities. The accuracy steadily increases, showing the model's ability to recognize patterns and make accurate classifications. Overall, the model successfully learns and performs well on all datasets, capturing their unique characteristics and achieving high accuracy values. In the test phase (as shown in Table 2), the CNN model demonstrates high accuracy and strong performance on the MNIST dataset, achieving an accuracy of 0.9917, along with impressive precision, recall, and F1 score values. The Fashion MNIST dataset also performs well with a slightly lower accuracy of 0.9112. However, the CIFAR-10 dataset shows moderate performance with an accuracy of 0.7066, while the CIFAR-

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100 dataset exhibits lower accuracy at 0.3806. These results emphasize the varying complexities and performance levels of the model across different datasets.

Table 1. The training processing of proposed CNN the different dataset

Epoch	Mnist		Palm		Fashion-Mnist	
	Loss	Accuracy	Loss	Accuracy	Loss	Accuracy
1	0.1225	0.9626	0.9869	0.4450	0.4427	0.8372
2	0.0410	0.9873	0.7005	0.4850	0.2953	0.8901
3	0.0269	0.9915	0.6943	0.5150	0.2463	0.9081
4	0.0184	0.9941	0.6937	0.4750	0.2135	0.9194
5	0.0139	0.9954	0.6940	0.4900	0.1852	0.9303
6	0.0104	0.9961	0.6906	0.5300	0.1598	0.9399
7	0.0078	0.9973	0.6911	0.5250	0.1383	0.9478
8	0.0074	0.9976	0.6948	0.4300	0.1182	0.9548
9	0.0063	0.9980	0.6885	0.5300	0.1036	0.9617
10	0.0067	0.9978	0.6886	0.5300	0.0875	0.9673

Epoch	Cifar10		Cifar100	
	Loss	Accuracy	Loss	Accuracy
1	1.3845	0.5050	3.5942	0.1574
2	1.0123	0.6465	2.8837	0.2873
3	0.8519	0.7036	2.5769	0.3480
4	0.7265	0.7465	2.3448	0.3962
5	0.6158	0.7852	2.1560	0.4367
6	0.5135	0.8212	1.9888	0.4744
7	0.4198	0.8520	1.8451	0.5061
8	0.3369	0.8828	1.7100	0.5359
9	`0.2628	0.9074	1.5817	0.5664
10	0.2068	0.9296	1.4598	0.5973

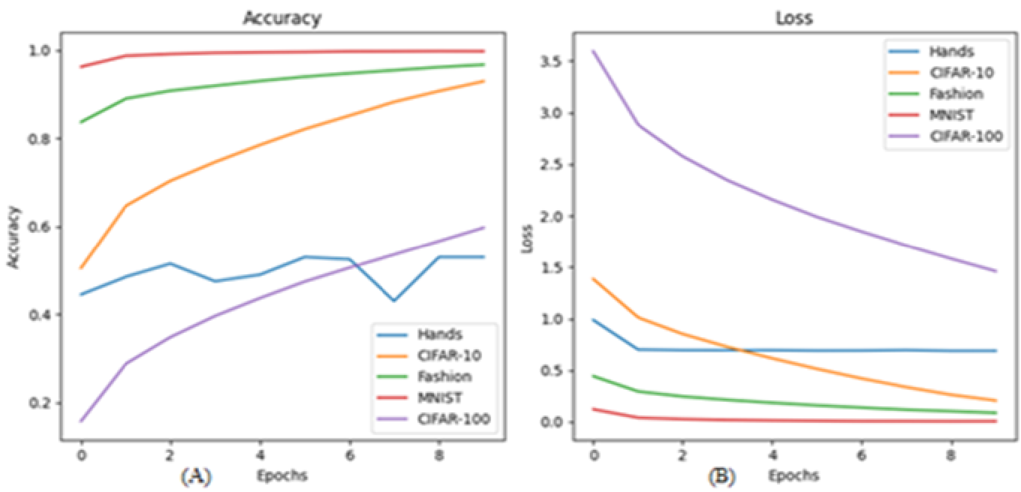

Figure 5. The training process with different dataset were. (A) compare base on accuracy with different dataset, (B)compare base on loss with different dataset

Table 2. The performance of proposed model

Dataset	Accuracy	Precision	Recall	F1 Score
Plam	0.52	0.52	0.52	0.52
Mnist	0.9917	0.991738	0.9917	0.991695
fashion mnist	0.9112	0.911196	0.9112	0.910681
cifar10	0.7066	0.710135	0.7066	0.707616
cifar100	0.3806	0.389027	0.3806	0.37464

Hash generation involved using a cryptographic hash function to convert CNN model predictions into unique hash values, ensuring safe and distinctive representations of input data. This process ensures safe and distinctive representations of input data, as hash functions resist collisions, making it highly unlikely for different inputs to produce the same hash value. The fixed-length hash representations enable tasks like image identification, similarity testing, and integrity checking based on the predictions from the CNN model. The hash generation process plays a crucial role in creating secure and efficient representations, allowing for easy identification and retrieval of similar examples in various applications as shown in Table 3.

Table 3. Hash Values for Images in Different Datasets based on proposed CNN

Dataset		Hash
Mnist	0	0a1ad3923faa1494445d83a8ac43f5ffdb3eeb40b39a14f91c6a3850693d8a02
	1	ec2edef02926ccece297621c1c91875f6d93405aef13e59b83a6f7f31ab18ca2
	2	9311999edceff2ca4b9b1ecbe543732f961ebfc35796c9003e7c9ad226f7d0ee
	3	8b60299da1d8d8fcfc9003e9a1585f1aed022144826cdb60f109e6cba695ba8c
Fashion-Mnist	0	dc12bcd9079341f98ee7bdd881ba41bab974410c92a69613238b088aee0e7c5a
	1	46a0e7cec1eec377b44a3375b8433efbfdf1787e108af8fa815be04b0d35e516
	2	752a329659db826b84d95ef552e320a0ecd3527c876c0677f467e251508cc64e
	3	ad2b32dc4fdd7352d0c3305ff1cf857d2011f65e3af8d92d345516a5f2315bbe
Cifar10	0	b4e9cf9f27b13d1363df1bd9d43b5c976a9147d38ebbe7410b623560f612c0f4
	1	17a38df1d11e78a10d7b585382762fa9a8edc2cb301489a8807e526f80f6a874
	2	a44f4cf80d4357164cbd789ef339b8604bae34cf62f686d8844d04d5a8db21a4
	3	377f2779362e118bc9cc87b149c27ccdbcafad80d05b045964be943130bb0b02
Cifar100	0	5d1b6787ab9de2323f3a78a347f0ca9e6017ad7de5481045aebb0f76a446345b
	1	cc4fdb4dc7c5632831b4962dfc45d6c03615b8ad7a7317920c20660fdae3515e
	2	e1ca9d4229d67e434770609ada410778c8c292bd8ee7e4c7f0d8b21d452c6abc
	3	51f969a92606d2064777af8a6975f0a5bf8ec28be09a7d497514dd2f5e7f795c
Palm	0	825828dfba849d4de34bdbcc7dbdbc77c1b862e665dc53fe2e3613d9bec0dd23
	1	03aca35b841f021a5f03c1e52f4c1ae6123b85d04ffd9c2ad37edbe2ede079cb
	2	2719a45b9bdd43637e2d581a3a3d8e132dc3e08651d900fd120e908649645bd6
	3	450603ba0e836fa2ad53289b56ca7532b7c5c11fd57f5facbe28be0ee6f38754

CONCLUSION

The proposed DeepRing is an advancement in tackling with several crucial issues associated with predictive modeling which includes problems regarding the model interpretability, vulnerability to data falsification, and imbalanced nature of some of the models. DeepRing aims at increasing the level of prediction integrity by applying the idea of CNNs and using blockchain to increase privacy, as well as to decrease potential bias and unfairness in predictive modelling, which in its turn, will lead to the enhancement of ethical standards, reliability, and accountability. This study involves the iterative training of a CNN model on five diverse datasets, including CIFAR-10, Fashion-MNIST, MNIST, CIFAR-100, and a Hands dataset. The CNN architecture incorporates Conv2D layers, MaxPooling2D layers, and Dense layers, with training metrics such as accuracy and sparse categorical cross-entropy loss monitored, and the Adam optimizer employed. Notably, DeepRing achieves high accuracy on MNIST (0.9978) and plam (0.5300) and Fashion MNIST (0.9673), while exhibiting moderate performance on CIFAR-10 (0.9296) and lower accuracy on CIFAR-100 (0.5973). The hash generation process emerges as a crucial component in securing and effectively representing input data, enabling tasks like similarity testing and image identification based on the CNN model's predictions. The implementation of a blockchain ensures tamper-proof storage of prediction hashes, placing a premium on accountability and transparency throughout the prediction process. Results from the study demonstrate the effectiveness of DeepRing in improving accuracy and enhancing model performance across various datasets. However, it is acknowledged that further development and validation are imperative for the successful implementation of the model. This underlines the ongoing commitment to refining DeepRing's capabilities and addressing any potential limitations, thus advancing the application of this approach in predictive modeling with a focus on integrity, security, and fairness.

SUPPLEMENTARY MATERIAL

None.

AUTHOR CONTRIBUTIONS

Methodology and software, Narjis Mezaal Shati; validation, analysis, writing—review and editing, Sura hamed mousa; investigation, and data curation, Nageswari Sakthivadivel.

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None.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at
https://www.cs.toronto.edu/ kriz/cifar.html
https://www.tensorflow.org/datasets/catalog/fashion_mnist
https://www.kaggle.com/datasets/haohaoxuexiba/hands-plam

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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