IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 17 September 2023, accepted 14 October 2023, date of publication 7 November 2023, date of current version 20 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3330914

RESEARCH ARTICLE

Block-Deep: A Hybrid Secure Data Storage and Diagnosis Model for Bone Fracture Identification of Athlete From X-Ray and MRI Images

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This work was supported by the Center of Excellence in Information Assurance (CoEIA), King Saud University.

ABSTRACT A human adult's skeleton is made up of 206 bones that perform a variety of vital biological tasks like safeguarding the internal organs and preserving vital nutrients. Bone fractures in adult's particularly in athletes can lead to minor sports injuries or even potentially fatal ones for which a sports injury specialist may be needed for treatment. The traditional methods of bone fracture detection are costly and time consuming and may leads to in-accurate results due to fault in the diagnostic machines. On the other hand, machine learning methods have found widespread use in bone fracture detection using X-ray or MRI images. However, all such methods haven't any proper security mechanism to athlete data that leads to theft, fraud and misuse of sensitive information. Therefore, with the correct fracture detection processes there also exists a strong security measure to stop unauthorized people from accessing or changing the data. In this research a hybrid model based on blockchain and deep learning has been proposed to diagnose the bone fractures as well as protection of the confidential data of the athletes. The key steps of the proposed work are data collection, blockchain based data security and transformation, feature extraction through Capsule Network, final classification using Visual Transformer based transfer learning. From the experimental evaluation and comparison with the state-of-the-art methods, it has been observed that the performance of the proposed work is excellent in terms of accuracy, with the value of 95.01%, 94.04 and 96.25% on different dataset respectively.

INDEX TERMS Bone fracture, blockchain, capsule network, MRI, machine learning, X-ray, visual transformer.

I. INTRODUCTION

The human body is made up of a variety of bone structures. The majority of bone fractures are the result of being a catastrophic fall during playing or running. Because of their brittle bone structure, elderly persons have an increased chance of fracturing a bone [1]. The detection of bone fractures is critical for sportsmen and sports enthusiasts. Accurate and quick detection of bone fractures is critical for athletes to obtain prompt medical care. Early detection can help sportsman to prevent more injury, reduce difficulties and speed up recovery. While fractures that go untreated or are mismanaged can result savior issues such as delayed healing, non-union (bone failure to mend), malunion (healing in an incorrect alignment) and subsequent injuries [2].

The physical health of professional athletes affects both their work and way of life. An athlete's career trajectory is protected by accurate fracture identification and effective treatment. Whereas, a fracture can be mentally difficult for athletes, hurting their self-esteem and general well-being. Anxiety and worry brought on by the injuries are reduced by prompt and efficient management [3]. Accurate diagnosis enables efficient treatment, which in turn can speed up an athlete's return to play. Moreover, Proper detection and

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Liu.

management prevent long-term impairments that could compromise an athlete's performance and quality of life [4]. It ensures that players heal quickly and return to their sports endeavors with few setbacks.

It is essential to protect athlete data while identifying bone fractures because this data includes sensitive and private medical information as well as diagnostic images [5]. The privacy and confidentiality of athlete health-related data are protected by maintaining strong security measures. Athlete data breaches can result in identity theft, fraud and the inappropriate use of private information. There always exists a need of strong security procedures to ensure that no other parties can view or change the information in any way. As a result, trusting medical professionals and organizations with the athletes' health information is crucial, which is why alternative diagnostic methods are preferred [6]. Damage to the athlete's relationship with their healthcare providers can result from breaches in data security.

The use of cutting-edge machine learning algorithms is widespread in medical diseases diagnosis. Computer-based methods use X-ray or MRI images in the field of medical diagnostics to identify broken bones [7]. However, all such methods doesn't have any proper security and authentication mechanism to secure sensitive data. Additionally, these bone pictures frequently have noise, necessitating the use of a suitable procedure to reduce noise and improve image details [8]. Therefore, obtaining a bone fracture model for athletes is crucial. This research work provides accurate and discreet bone fracture diagnoses with secure data storage and transformation. The proposed work is based on blockchain based secure data storage, feature extraction and bone fracture identification.

A. RESEARCH CONTRIBUTIONS

The key contribution of the proposed research are as follows:

- A blockchain based secure data storage mechanism that gives protection to medical information, diagnostic images and personal credentials. Maintaining strong security measures that safeguards the privacy and confidentiality of athletes' health-related information.
- The key contribution of this work is to propose a deep learning model that correctly identifies bone fractures in comparison to standard medical diagnosis methods that are costly and time-consuming, but are critical for athletes' long-term well-being, performance, and overall quality of life.
- Experimental evaluation revealed the excellent performance of proposed work with accuracy value of 95.01%.

The rest of the manuscript is divided into five sections, which are as follows: Section II provides the literature review. Section III discusses the proposed methodology, Section IV discusses the result and evaluation, the conclusion and future research are summarized in section V.

II. LITERATURE REVIEW

The literature review section is divided into two broad categories that are secure storage and transformation via blockchain and image based healthy and fractured bones classification.

A. BLOCKCHAIN-BASED SECURE STORAGE OF MEDICAL DATA

The usage of blockchain technology in healthcare has a big effect due to its security authentication process, fast transformation and its open access to everyone. The work of Azaria et al. [9] proposed an Electronic Health Records (EHR) called MedRec to manage the health related information of different medical institutes. This was a decentralized blockchain system that provides safety and security for confidential data of patients. The key steps of their proposed MedRec were assigning administrative rights, permissions, and the ability to share data within the system. A hybrid blockchain model was designed by Medblock [10] to protect Electronic Medical Records (EMR). There model was based on endorsement nodes, sorting nodes and submission nodes. In addition to this, a consensus algorithm was used to take the final decision for suitable node selection. Conceico et al. [11] proposed a generalized blockchain technology to store EHR data for patients. Yang et al. [12] suggested a blockchain-based EHR design that protects the integrity of data by logging all events on the blockchain that helps to protect misuse of data. Kushch et al. [13] used blockchain tree as a unique way to store electronic medical data on the blockchain. Their contribution helped to link the sub-chains with important patient information, like diagnostic records, to the main chain.

B. BLOCKCHAIN-BASED SECURE SHARING OF MEDICAL DATA

Blockchain technology is often used for secure data sharing in addition to its ability to store data safely. The medical field has gotten a lot of attention for its study into and use of blockchain applications, which becomes a challenging research area and has been targeted by many research institutions around the world. Xia et. al. [14] came up with "men shared," a blockchain-based system that is meant to reduce the risks of data theft during data sharing process. Their approach solved the problem of secure sharing of medical information between people who don't trust each other. Zhang and Lin [15] proposed a blockchain-based system for sharing medical data. In their work, hospitals were used as a private blockchain to store health information about patients, while a group blockchain protected security for each hospital indices. Rachamalla et al. [16] created a safe and open platform for sharing medical data by combining artificial intelligence and blockchain technology. Their platform was based on the fact that blockchain is built on openness to set up data tracking that can't be changed.

Liu and Li [17] used a hybrid method that was based on blockchain technology and cloud storage for sharing data that protects medical privacy. Their method involved backing up the original medical data on cloud, indexing it in the blockchain, with the fact that the blockchain can't be changed to stop unwanted modifications. Qiao et al. [18] defined a new way for medical alliance chains to communicate each other in safe and autonomous way. Their technique reduced the time complexity of communication and gives medical alliance chains facility to communicate each other quickly.

C. X-RAY AND MEDICAL IMAGES BASED BONE FRACTURE DETECTION

The human body is made up of many types of bones, and bone fractures are frequently caused by situations such as car accidents or falls. Because of weakening bones, the aged population is at a higher risk of bone fractures [19]. Doctors and physician usually use X-rays or MRI (Magnetic Resonance Imaging) scans to identify fractured bones [20]. However, detecting small bone fractures might be difficult for medical experts. The conventional methods for identifying fractured bones are time-consuming and prone to inaccuracy when the medical equipment is faulty. Thus, the computer-based system are prominent to reduce the diagnosis time and accurate for fractured bones detection [22].

The topic of bone fracture detection have been widely discussed. The work of Dimililer and Kamil [23] have used ANN (Artificial Neural Network) based deep learning model to classify fracture bone. However, they did not distinguished between healthy and damaged bones. In a study by Yang et al. [24], a contour feature from an X-ray picture was used to identify fractured bones. Their system's accuracy was 85%, although there technique needed more optimized similarity measures for improvement. The Gray-Level Co-occurrence Matrix (GLCM) was used by Wang et al.'s [25] to extract textural information for identifying bones as fractured or non-fractured. They utilized image characteristics with a resolution of 410×500 to do the said. Their system had a classification accuracy of 86.67%.

This work is a deep learning based classification model that classify healthy and fractured bones. The key steps of the proposed work are: a blockchain based data storage and transformation from various medical hospitals and sports center. Data preprocessing, feature extraction and deep learning based classification. The performance of the proposed work has been tested on 3000 unique pictures of different kinds of human bones. Consequently, using a standard evaluation measure such as precision, recall f-score, accuracy and 5-fold cross-validation method, the suggested model gets an admirable classification accuracy of 92.44% for both healthy and fractured bones.

III. PROPOSED METHODOLOGY

This section discusses the proposed methodology for securing the confidential data of athletes followed by diagnosis model for bone fracture identification. Figure 1 shows the schematic diagram of the proposed architecture that is composed of data collection, blockchain based secure data storage and transformation, preprocessing, deep learning-based feature extraction and fracture diagnosis. The detail of each phase has been shown in Figure 1.

A. DATA COLLECTION

Three different datasets have been obtained from different organizations of sports, that are International Islamic University (IIUI) Directorate of Sports, FracAtla fracture classification dataset, Leg fracture dataset obtained from the electronic database of Pakistan Institute of Medical Sciences (PIMS). The IIUI dataset was composed of almost 3,222 students record with their confidential information and bone fracture history that were obtained on public request with the assurance that no data will be publically accessed. The FracAtla dataset is the X-Ray images of fracture bones with different dimensions. This dataset was also obtained by public request and it contains 4,083 X-ray images. In the last, the NLM dataset includes the 2,477 nasal fracture record of patients that were registered for their medical treatment in the year 2020 to 2023. The dataset breakdown is shown in Table 1.

B. PROPOSED BLOCKCHAIN MODEL FOR SECURE DATA STORAGE

The proposed blockchain architecture is based on the mechanism that intended to guarantee the confidentiality, integrity, and accessibility of this delicate medical data. This design uses blockchain technology to provide a safe and open data environment that is tailored to bone fracture records. The blockchain technology are mostly used to secure the confidential medical record due to its secure access, fast transformation and decentralized data-sharing and application systems. Whereas, the traditional approaches to medical information management entails a centralized system for data storage. However, the disadvantage of this strategy is its highly concentrated control over information management, which impedes effective information exchange. The concept of distributed ledgers in blockchain technology helps in. multiple entities collaborate to uphold and oversee file information entry. This collaborative monitoring, helps in concurrency control during the multiple department's access to the data.

In the very first phase the data on bone fractures is safely kept in individual blocks on the blockchain. Each block contains encrypted information on the patient, fracture type, therapy, and other pertinent details. Encryption ensures that sensitive data remains private and that only authorized parties can access it. After which the essential data about bone fractures can be accessed, shared and validated using smart contracts that are programmed with specified business logic. These agreements automate the application of certain rules, ensuring that data access and sharing only occur in accordance with established norms. The insertion of new blocks to the blockchain is verified by a Proof of Work (PoW)

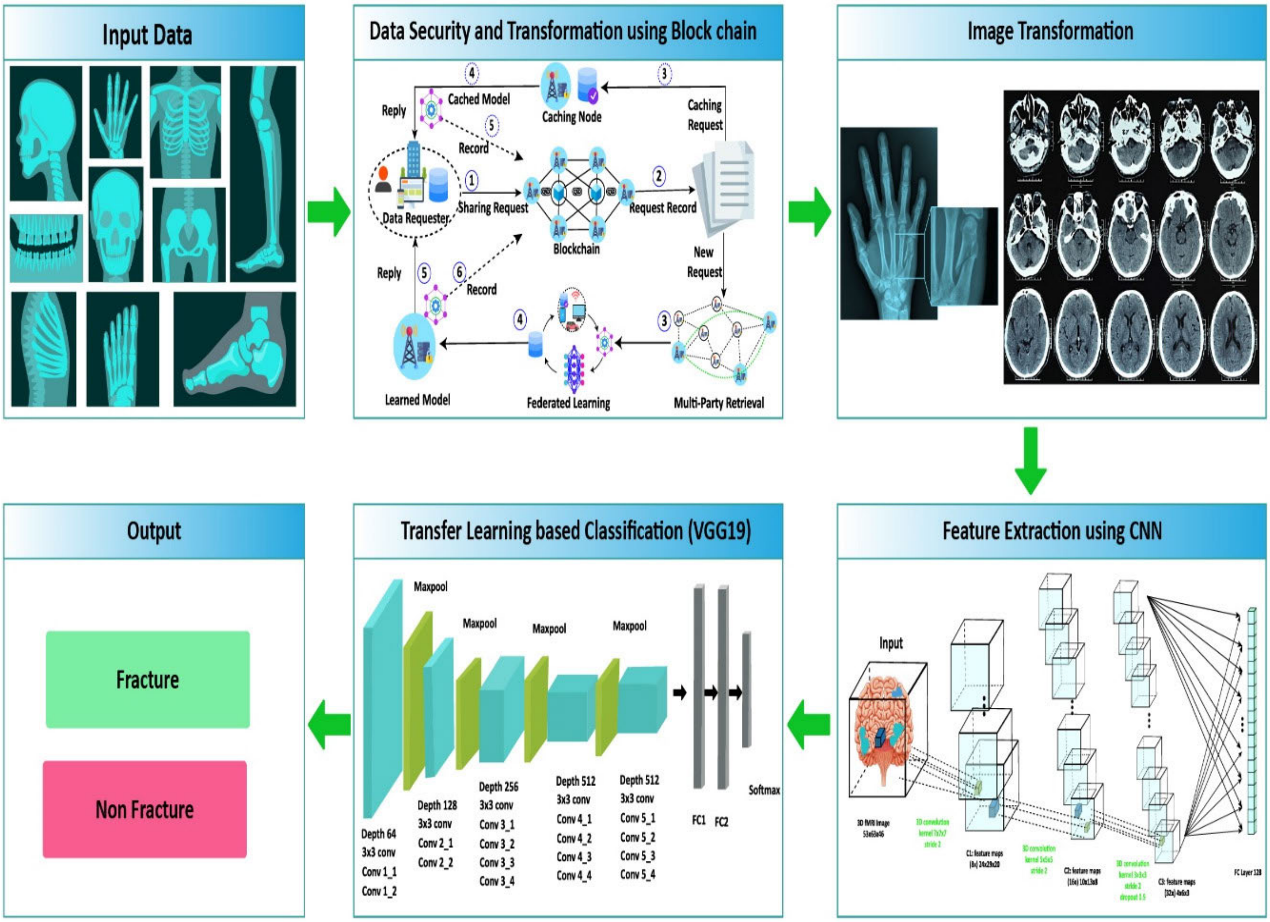

FIGURE 1. Block-deep architecture for bone fracture diagnosis and confidential data storage.

TABLE 1. Dataset description.

Sr. No.	Dataset Name	Description	Link
1	DS-I	IIUI Directorate of Sports	https://www.iiu.edu.pk/?page_id=18201
2	DS-II	FracAtlas	https://doi.org/10.6084/m9.figshare.22363012
3	DS-III	NLM	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8976798/

consensus process [26], that makes sure that before the data is added to the ledger, everyone agrees on its accuracy. The distributed nature of the blockchain network eliminates a single point of failure and improves security. Redundancy and data loss are ensured since each node has a copy of the whole ledger.

As far as the access control is concerned, the cryptographic keys are used to implement access control measures. Participants have unique keys that provide them access to their relevant data, such as healthcare providers and patients. Only permitting specific information to be viewed by authorized individuals ensures privacy.

Data about bone fractures may be easily audited and traced by blockchain's transparency. An audit trail that may be checked as needed, is produced by each modification or access to the data being recorded in an immutable manner. In order to provide seamless data sharing between various healthcare providers while protecting data security, the proposed architecture helps to interact with already-existing medical systems and databases.

C. ACCESS CONTROL

Combining Blockchain and Federated Learning for Medical Data: A highly secure and privacy-preserving environment for medical data storage and transformation can be developed by combining blockchain technology and federated learning. The immutability and integrity of the training process and model updates are ensured by blockchain. Federated learning protects patient privacy while allowing healthcare practitioners to cooperate on model development without jeopardizing sensitive data.

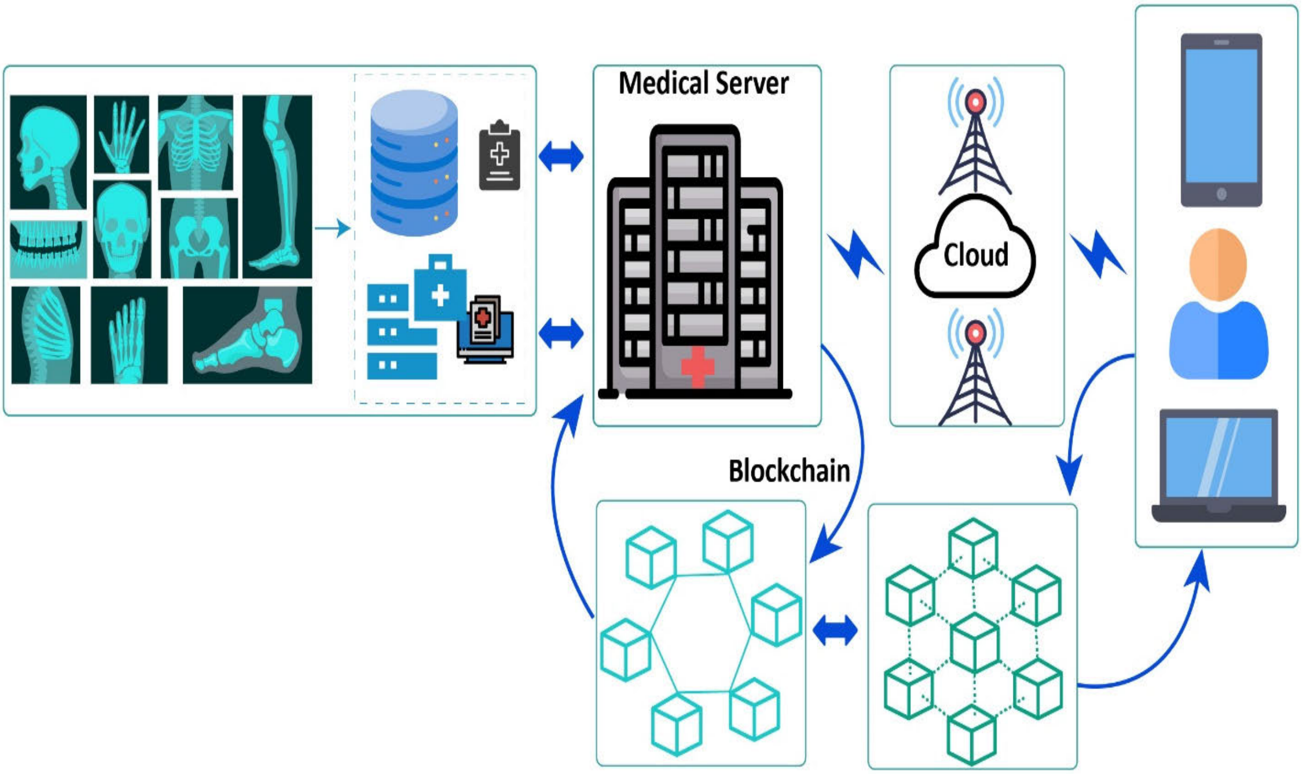

FIGURE 2. Blockchain architecture for securing the confidential data of athlete.

Blockchain can be utilized to manage access control, permission management, and audit trails of data usage and model updates in this combined method. Federated learning guarantees that medical insights be extracted from a variety of data sources without the need for raw data to be shared.

Finally, the combination of blockchain and federated learning has the potential to alter medical data management by providing a safe, transparent, and privacy-conscious framework for storing, sharing, and transforming sensitive healthcare data.

D. PROPOSED DEEP LEARNING MODEL FOR FRACTURE DIAGNOSIS

In this section, the proposed Bone fracture detection technique from an X-ray image of the different parts of body having bone has been proposed. Initially, the description of the main dataset has been outlined, while later on, the proposed Block-Deep has been elaborated.

1) DATA AUGMENTATION AND SCALING

All x-ray images of different body parts were stored in 3 datasets and loaded into a deep learning pipeline for scaling to a fixed size of 260 X 260 pixels. The Numpy array used to label the data to indicate a FRACTURE and Non-FRACTURE case for every image in the dataset. In this work, zero stands for FRACTURE images and one for Non-FRACTURE images. After the labeling, data augmentation is applied for creating new training samples that can help to improve the robustness and generalization of the proposed deep learning models. During data augmentation the X-ray images were simulated into various angles (e.g., 90, 180, 270 degrees) that helped the model learn to recognize fractures from different angles. After which, the X-ray images were resized and cropped to focus on their specific regions of interest in order to clearly sketch the fracture's abnormalities [27].

In addition to the above, the brightness and contrast of X-ray has also been applied to mimic the different lighting conditions of images. In order to further improve the image quality by removing noise, a real-world imperfections simulation have been applied. To enhance the image resolution, a histogram equalization is applied that identify subtle out the fractured regions. Finally, all the images are adjusted using padding, zooming and color channel variation mechanism that apply typical grayscale and color encoding technique to clearly portray each X-ray image. It's important to strike a balance between augmentation and preserving the medical relevance of the data. Augmentations that drastically alter the appearance of X-ray images might introduce unrealistic features or artifacts that could mislead the model.

2) FEATURE EXTRACTION

There exist various deep learning models for image based feature extraction such as CNN, GNN and RNN. Among all

Algorithm 1 CapsNet Procedure

```
class CapsuleLayer:
    def __init__ (self, num_capsules, num_route_nodes, input_dim, capsule_dim):
        self.num_capsules = num_capsules
        sclf.num_route_nodes = num_route_nodes
        self.input_dim = input_dim
        self.capsule_dim = capsule_dim
        self.W = initialize_weight_matrix(num_capsules, num_route_nodes,
        capsule_dim, input_dim)
    def squash(self, vector):
        squared_norm = norm (vector, axis=-1, keepdims=True) * * 2
        scale - squared_norm / (1 + squared_norm)
        squashed_vector = scale * vector / norm (vector, axis=-1, keepdims=True)
        return squashed_vector
    def forward(self, input):
        input_reshaped = reshape (input,(-1, self.num_route_nodes, self.input_dim))
        predictions = matmul (input_reshaped, self.W)
        output_capsules = self.squash(predictions)
        return output_capsules
class CapsuleNetwork:
    def __init__(self):
        self.conv_layer = ConvolutionalLayer ()
        self.primary_capsule_layer = CapsuleLayer ()
        self.digit_capsule_layer = CapsuleLayer ()
    def forward(self, input):
        conv_output = self. conv_layer(input)
        primary_capsules = self.primary_capsule_layer(conv_output)
        digit_capsules = self.digit_capsule_layer(primary_capsules)
        return digit_capsules
```

of these, the Capsule Networks (CapsNets) are a relatively novel architecture designed to address some of the limitations of traditional Convolutional Neural Networks (CNNs) in capturing spatial hierarchies and handling transformations within images [28]. CapsNets aim to improve the way features are extracted and represented by introducing "capsules," which are groups of neurons that work together to encode various properties of a feature [29].

Algorithm 1 shows the step by step procedure of CapsNet that starts with a series of convolutional layers in the initial stages, similar to CNNs. These convolutional layers are used to extract low-level features from the input X-ray image, just like in CNNs. After the capsule creation, unlike CNNs, where individual neurons respond to specific features (edges, textures, etc.), capsules are designed to capture richer information. Each capsule represents a specific feature and encodes not only its presence but also its relationship like pose, orientation, and association with other features. The pose and activation of each capsule produces an output vector that encodes both the probability of the feature's presence and additional information about its properties. This information includes attributes like the position, orientation, and size of the feature within the image. This is in contrast to CNNs, where features are activated independently of their spatial relationships.

When the capsule is initialized, the next phase is its dynamic routing that allows capsules to collaborate and determine the next level features based on the information provided by initial level capsules. Dynamic routing iteratively adjusts the weights between capsules to strengthen connections that agree on the presence and properties of features. Through dynamic routing, capsules at one layer send information to the capsules in the next layer, integrating their individual outputs to form a richer representation of features. This is in contrast to max-pooling in CNNs, where only the strongest feature in a region is considered only. Finally, each capsule represents a specific class or attribute, and the length of its output vector represents the probability of the presence of that class or attribute in the input image. Whereas, at the end dynamic routing process helps capsules converge to get accurate representations of features.

3) MODEL TRAINING AND VALIDATION

In order to start the training phase of selected Block-Deep model, the preprocessed dataset was split with the ratio of

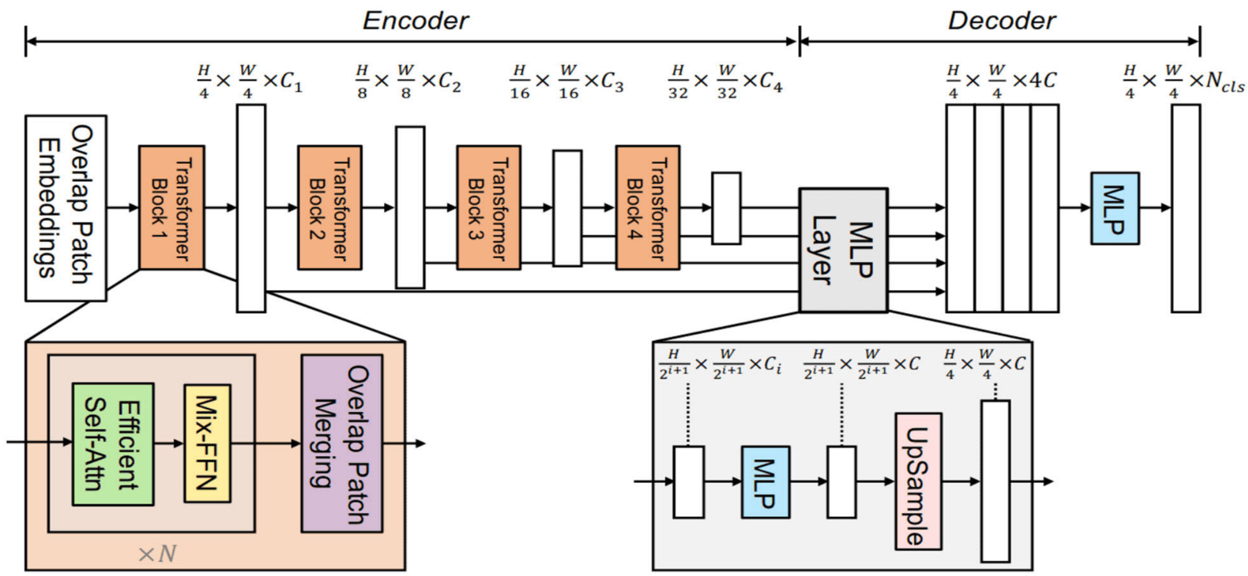

FIGURE 3. The working mechanism of proposed transfer learning.

80-20% by using train_test_split function from sklearn. model selection library. In which, 20% of image data used for testing phase and remaining 80 % for training set. Later on, the deep learning classifier has been validated with the support of subsample random selections of training image data. At the end, the evaluation metrics have been applied to show the recorded performance on the test set.

4) TRANSFER LEARNING METHOD

The classification phase of Block-Deep is based on transferring learning that train the model on initial level features and then update itself on simultaneous task, that need some minor level adaptation to the new task. Although CNN is to be considered as the most usuall deep learning model for transfer learning but in this work, the Vision Transformer ViT is used, that is a transformer-based architecture which has shown promising results for X-ray image classification. It divides the input image into fixed-size patches and processes them using transformer blocks.

Figure 3 describe the working of ViT based Transfer learning that start with Patch Embedding. Instead of treating an entire image as a single input, ViT divides the image into fixed-size non-overlapping patches. Each patch is then linearly embedded into a vector using a learned linear projection. These patch embeddings serve as the initial input to the transformer. After which, Positional Encoding has been performed that is Just like in the original transformer [30]. The ViT uses positional encodings to provide the model with information about the position of each patch in the image. This helps the model understand the spatial relationships among patches.

The Transformer Encoder phase which is next to Positional Encoding consists of multiple self-attention layers and feedforward neural networks. The self-attention mechanism allows the model to capture global relationships between different patches, whereas, the feedforward layers' capture local features within each patch [31], [32], [33]. To enable the model to make classification about different classes, a special "class token" is added to the patch embedding's. This class token is treated as the starting point for the classification process and is combined with the patch embedding's for final predictions. Finally, the class token, along with the patch embedding's, passes through the transformer encoder to capture both initial and next level features. The resulting representation is then fed into a classification head, typically consisting of one or more fully connected layers, to make final classification.

IV. EXPERIMENTAL RESULTS AND EVALUATION

A thorough analysis of the findings is provided in this section. The accuracy and efficiency of the suggested system were assessed through a thorough series of trials. The operational efficacy of the suggested method was evaluated using three distinct datasets. The results of the experimental investigation showed that the performance of the suggested strategy outperformed other current state-of-the-art methodologies

A. BASELINE METHOD

By contrasting the proposed model with the reference models given below, we assess the performance of the suggested model using the data sets shown in table 2.

- Krogue et al. [34] proposed a technique that were based on DensNet A deep learning–based object detection model.
- Yadav et al. [35] proposed a deep learning model SFNet for Bone Fracture Detection and Classification.

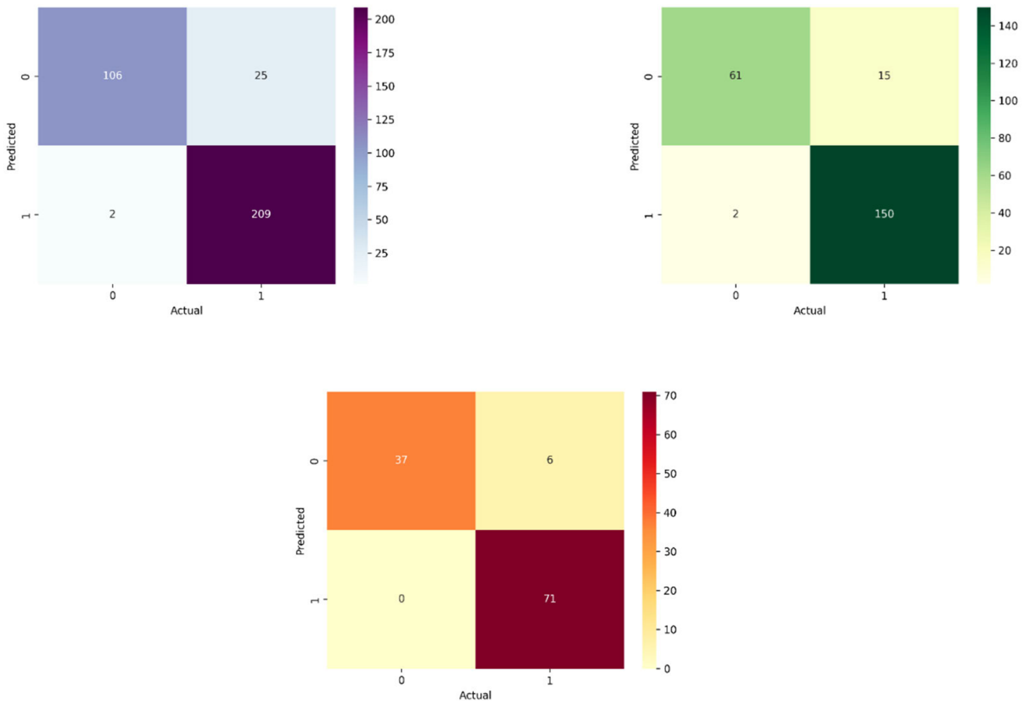

FIGURE 4. Confusion matrix of proposed block-deep model on DS-1, DS-II and Ds-III.

- Chen et al. [36] proposed a deep-learning (DL) model for identifying fresh VCFs from digital radiography.

B. PERFORMANCE MATRICES

The effectiveness of the suggested strategy is assessed using three different types of performance criteria. The detail of each measure has been provided in below subsections.

- ***F-measure and Confusion Matrix***

The proposed model was evaluated using classification metrics that included precision, recall, and F1 score. Equations (1), (2), (3), and (4), as shown at the bottom of the page, outline how to calculate each of these metrics.

- ***Matthews Correlation Coefficient (MCC)***

The Matthews Correlation Coefficient (MCC) is frequently used to assess binary classification ability. The MCC value, a unique numerical representation, can be obtained by examining a confusion matrix's features. Equation 5 provides an example of how to calculate MCC.

$$\mathrm{MCC} = \frac{(\mathrm{TP} * \mathrm{TN} - \mathrm{FP} * \mathrm{FN})}{\sqrt{(TP+FP)\,(TP+FN)(TN+FP)(TN+FN)}} \tag{5}$$

The MCC scale ranges from -1 to 1, which reflects the binary classification model's accuracy in predicting positive and negative occurrences while accounting for class imbalances. MCC values of 1 or -1 indicate flawless predictions. A score of 0 indicates that the MCC is unable to distinguish between positive and negative cases. In contrast, a negative MCC, such as -1, emphasizes the model's significant ineffectiveness.

- ***ROC Curve*** The ROC curve is constructed by plotting the true positive rate (sensitivity) versus the false positive rate (1-specificity) to illustrate the discriminatory power of a binary classification model across a range of probability thresholds. This graphical representation permits a thorough

$$\text{Accuracy} = \frac{sum(True\ Positives, True\ Negatives)}{sum(True\ Negatives, False\ Positives, True\ Positives, False\ Negatives)} \tag{1}$$

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{2}$$

$$Precision = \frac{count(True\ Positives)}{sum(True\ Positives, False\ Positives)} \tag{3}$$

$$Recall = \frac{count(True\ Positives)}{sum(True\ Positives, False\ Negatives)} \tag{4}$$

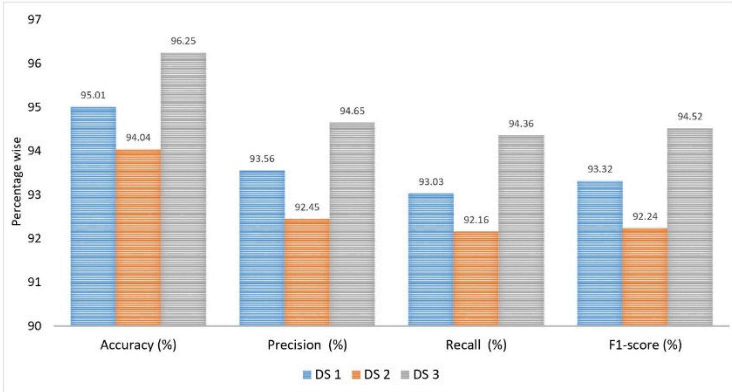

FIGURE 5. **Performance evaluation of the proposed deep learning model.**

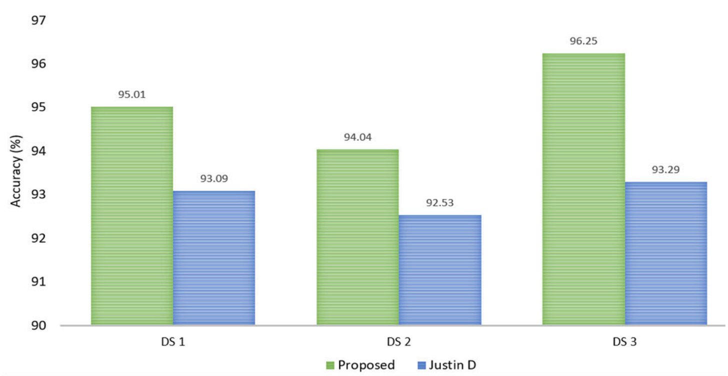

FIGURE 6. **P Comparative analysis of bloc-deep Justin D on DS-I, DS-II and DS-III.**

evaluation of the model's ability to differentiate between positive and negative instances.

C. EXPERIMENTATION RESULTS

The initial experiment demonstrates the effectiveness of the recommended approach for diagnosing bone fractures by evaluating its precision, accuracy, and recall. Figure 4 depicts the confusion matrix of proposed Block-Deep on different datasets. The demonstration unquestionably described that the proposed method yielded exceptional results across all datasets, achieving remarkable precision, recall, and accuracy for each unique dataset.

Figure 5 shows the performance evaluation of Block-Deep in terms of precision, recall, F-Score and accuracy. When applied to DS 1, the proposed technique demonstrated precision of 93.56%, recall of 93.03%, accuracy of 95.01%, and an F1-score of 93.32, indicating remarkable results. Similarly, in the case of DS 2, the proposed approach exceeds expectations, attaining an accuracy of 94.04%, precision of 92.45%, recall of 92.16%, and F1-score of 92.24, all of which are very motivating. Furthermore, on the DS 3 dataset, the suggested technique performed well, with accuracy, precision, recall, and F1-score values of 96.25%, 94.65%, 94.36%, and 94.52%, respectively. These data convincingly illustrate the suggested method's efficiency and extraordinary prowess in terms of precision, accuracy, F1-score, and recall for the bone fracture detection task.

The proposed Block-Deep has also been compared with the baseline methods described in section IV-A. In the very first attempt the Block-Deep has been compared to the work of Justin D et. al. on DS 1, DS 2, and DS 3. The results in figure 6 showed that Block-Deep outperformed the competition, with 95.01% accuracy on DS 1, 94.04% on DS-II and 92.53% for DS-III. This striking discrepancy highlights the clear accuracy advantage of the proposed Block-Deep.

In another experiment, the performance of the proposed model was compared with the work of Yadav, D. This comparison in Table 2 clearly indicate that Bloc-Deep completely surpassed the baseline work with 4% accuracy variation on DS-I, 7 % accuracy variation on DS-II and almost 8% accuracy variation of DS-III.

Last but not the least, the accuracy wise comparison of Block-Deep to all standard baselines has been depicted in Figure 7. Where the findings strongly suggest that Block-Deep perform well on almost all dataset. The key reason of the effective performance of Block-Deep is the utilization of blockchain and key techniques of deep learning. However, in order to confirm its benefits and determine its

TABLE 2. Comparison with proposed and baseline approaches.

Technique	Precision %	Recall %	F-Score %	Accuracy %
Performance Evaluation on DS 1				
Proposed Model	93.56	93.03	93.295	95.01
Baseline 4	94.22	91.02	92.62	91
Performance Evaluation on DS 2				
Proposed Model	92.45	92.16	92.035	94.04
Baseline 4	86.05	84.21	85.13	87.94
Performance Evaluation on DS 3				
Proposed Model	94.65	94.36	94.505	96.25
Baseline 4	89.66	86.22	87.94	89.90

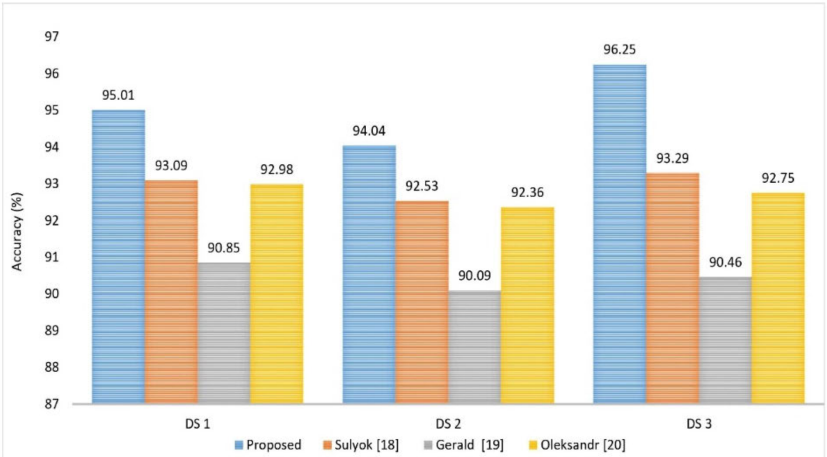

FIGURE 7. Accuracy based comparison of blok-deep with baseline approaches.

suitability for practical applications, more study and testing must be done.

V. CONCLUSION

The adult human skeleton, consisting of 206 bones, fulfills crucial roles like safeguarding organs and storing nutrients. Adult fractures, common among athletes, vary from minor sports wounds to serious injury that leads to life-threatening situations. The treatment of such injuries may include experts' advice who may recommend to limit the activities, bed rest or even discontinuation of sports. Traditional fracture detection methods are costly, time-consuming and may prone to inaccuracies due to diagnostic machine faults. Conversely, machine learning has revolutionized fracture detection using X-rays or MRI images. Yet, these approaches often lack robust security measures, exposing sensitive athlete data to risks like theft and misuse. To address these challenges, this research introduces an innovative hybrid Block-Deep model that tries to integrate blockchain and deep learning. The proposed Block-Deep is enough capable to not only accurately diagnoses bone fractures but also ensures the security of athletes' confidential information. The key steps of Block-Deep are data collection, blockchain based secure data storage and transformation, feature extraction using Capsule Network and final classification through Visual Transformer-based transfer learning. Upon experimental evaluation and comparison with prevailing methods, Block-Deep demonstrates exceptional performance. Achieving accuracy rates of 95.01%, 94.04 and 96.25% across distinct datasets reaffirms the superiority of our approach. The future work will focus on optimizing the hybrid model's computational efficiency to enable real-time diagnosis and exploring additional layers of encryption within the blockchain for enhanced athlete data security. Additionally, investigating the model's adaptability to diverse imaging modalities and expanding its application to other medical diagnoses holds promise for further advancement.

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