RESEARCH PAPER

Detection of Skull Damage in 3D Skull Models Using Hybrid Artificial Intelligence Techniques

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ABSTRACT
Accurate detection of skull damage is essential in forensic science, biomedical engineering, and trauma diagnosis. However, traditional diagnostic approaches rely heavily on manual interpretation and lack automation, leading to time delays and reduced consistency. This paper proposes a hybrid artificial intelligence framework termed SIDD-CNN-LSTM for automated skull damage detection using 3D skull models. The proposed system integrates geometric data transformation, pre-processing, segmentation, and dual feature extraction using both deep learning and handcrafted approaches. CNN layers extract high-level features, while LSTM performs sequential classification. Additionally, handcrafted features are extracted and classified using ANN, SVM, and Naïve Bayes for comparative analysis. Experimental evaluation on 480 skull models demonstrates superior accuracy. The findings highlight the effectiveness of hybrid AI techniques for reliable and automated skull damage detection.

Keywords: Skull Damage Detection, CNN-LSTM, Hybrid AI, Medical Imaging, Deep Learning.
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1. Introduction

The human skull is essential for preserving craniofacial structure, making its integrity critically important in medical, forensic, and anthropological applications. Skull damage, including fractures and structural deformities, often results from trauma, accidents, or pathological conditions, and successful diagnosis depends on precise detection, treatment planning, and post-event analysis. Traditionally, imaging modalities like computed tomography (CT), X-ray imaging, and 3D scanning techniques are used to diagnose skull injury. However, It takes a lot of work to manually interpret these pictures. , subject to human mistake, and a strong reliance on specialized knowledge, particularly in complex cases involving subtle or irregular damage patterns.

Given how quickly artificial intelligence are developing, (AI), automated diagnostic systems have gained significant attention in the examination of medical images. Convolutional neural networks (CNNs), in particular, have shown impressive performance in machine learning and deep learning techniques in detecting abnormalities in medical images, including fracture detection and disease classification. Despite these advancements, most existing approaches primarily focus on 2D medical images and often neglect the geometric and structural information inherent in 3D skull models.

Parallel developments in 3D modeling and surface registration techniques have enabled more accurate representation and analysis of craniofacial structures. More recent approaches based on discrete uniformization and geometric transformations have improved robustness in handling complex topologies and low-quality mesh data. However, these methods are generally applied for registration and reconstruction purposes rather than for automated damage detection, limiting their direct applicability in diagnostic systems.

Another important limitation in existing research is the lack of integration between deep learning–based automatic feature extraction and domain-specific handcrafted feature analysis. While deep learning models offer high accuracy and automation, they often lack interpretability and may fail to capture certain geometric or structural characteristics of skull damage. Conversely, traditional feature-based methods provide better interpretability but lack scalability and automation. Therefore, there is a need for a hybrid framework that combines the strengths of both approaches to achieve improved performance and reliability.

In addition, most current studies focus on fracture detection in 2D radiographic images, with limited exploration of damage detection in 3D skull models. Information loss and feature consistency become issues when 3D data is transformed into 2D representations. Furthermore, Long Short-Term Memory (LSTM) application and other sequential learning models networks remains underexplored in this domain, particularly for capturing spatial dependencies and improving classification demonstration.

This study suggests a unique hybrid artificial intelligence-based paradigm for the identification of skull damage in 3D skull models. The proposed approach integrates 3D-to-2D conversion, image preprocessing, region of interest (ROI) extraction, and a deep learning architecture combining LSTM and CNN for automatic feature learning and classification. Then the hybrid techniques used to evaluate multiple classifiers to ensure robust performance.

The following are this work's primary contributions:
(i) to develop a hybrid CNN-LSTM–based automated skull damage detection model,
(ii) integration of deep learning and handcrafted feature extraction techniques,
(iii) comprehensive performance evaluation using multiple classifiers and metrics, and
(iv) verification of the suggested method on a 3D skull dataset with different training–testing ratios.

2. Literature Review

Recent advancements in computer-aided diagnostic (CAD) technologies and analysis of medical images have significantly enhanced the automated detection of neurological disorders and craniofacial abnormalities. The techniques such as artificial intelligence (AI) and machine learning is mostly used to find out the disease like Parkinson's, Alzheimer's disease, and stroke by ischemic using imaging modalities like EEG and MRI [1]–[5]. These approaches typically involve feature extraction techniques such as discrete wavelet transform, texture analysis, and higher-order spectral methods, followed by DRT (dimensionality reduction techniques) including PCA (principal component analysis) and LDA (linear discriminant analysis) to modify computational efficiency [2], [3], [6]. Different machine learning techniques such as SVM, KNN, and Random Forest are applied for classification. In recent research, deep learning approaches, particularly CNNs, have shown improved accuracy and stability [4], [5], [7]–[9].

Furthermore, hybrid approaches that integrate signal processing techniques with machine learning models have drawn a lot of attention because of their enhanced feature representation capabilities. Genetic algorithms, Particle swarm optimization, and entropy-based feature selection these are the optimization techniques are widely used to identify the most discriminative features and reduce redundancy [6], [10], [11]. Despite these advancements, challenges such as limited dataset availability, variability in imaging quality, and poor generalization across different datasets continue to hinder the development of reliable diagnostic systems [1], [12].

Parallel research in the field of 3D skull reconstruction and registration has contributed significantly to applications such as forensic identification, craniofacial reconstruction, and anthropological studies. Traditional registration methods, including the Iterative Closest Point algorithm and Thin Plate Splines, are commonly used but suffer from limitations such as sensitivity to initial alignment, dependence on manually defined landmarks, and difficulty in handling non-rigid deformations [13], [14]. To overcome these limitations, advanced techniques based on conformal mapping and surface parameterization have been introduced, enabling the transformation of complex 3D skull geometries into simplified 2D representations while preserving intrinsic geometric properties [15], [16].

A major advancement in skull registration is presented in [17], where an automatic and reliable method using discrete uniformization theory is proposed. This approach employs dynamic Yamabe flow and Koebe's iterative framework to map complex skull surfaces onto planar domains with circular boundaries, followed by constrained harmonic mapping for accurate correspondence. The method is mathematically rigorous, fully automated, and robust to low-quality mesh data, making it ideal for practical uses. involving complex skull structures.

Recently, many studies have used deep learning methods to detect fractures from CT and X-ray images. CNN-based models have demonstrated high diagnostic performance, achieving strong accuracy, sensitivity, and specificity in skull fracture detection tasks [18], [19]. Advanced architectures such as attention-based CNNs and transfer learning models (e.g., InceptionV3) have further improved performance by enhancing feature extraction and generalization capabilities [22], [23]. Additionally, hybrid frameworks integrating conventional machine learning classifiers with deep learning-based feature extraction have shown promising results in improving detection accuracy and computational efficiency [24]. Alternative approaches, such as microwave-based skull fracture detection, have also been proposed for point-of-care diagnostics, offering portable and cost-effective solutions [25]. Moreover, recent studies highlight the broader impact of AI, 3D printing, and bioengineered materials in craniofacial reconstruction and surgical planning [20], while also identifying challenges related to model generalization, dataset bias, and clinical integration [21].

Despite the significant progress in both medical image analysis and skull modeling techniques, existing studies largely address these domains independently. Most research focuses either on disease diagnosis and fracture detection using imaging data or on geometric processing tasks such as skull registration. Limited work has explored the integration of these approaches for structural skull damage detection. Therefore, there is a need for a unified framework that combines geometric processing with hybrid artificial intelligence techniques. This research fills this void by proposing a hybrid CNN-LSTM-based approach integrated with conventional machine learning models to achieve accurate, automated, and robust detection of skull damage in 3D skull models, thereby enhancing performance in forensic and biomedical applications [1]–[31].

2.1 Limitations of Existing Work and Research Motivation

Despite significant progress in medical image analysis and skull-related studies, several critical limitations persist in existing approaches. Most of the current methods focus primarily on 2D imaging modalities and lack effective integration with 3D skull models, thereby failing to capture complex geometric and structural characteristics. Additionally, many studies rely either on deep learning-based automatic feature extraction or traditional handcrafted features independently, resulting in limited utilization of hybrid feature representations. Another major concern is the poor generalization capability of existing models across diverse datasets, mainly due to variations in imaging conditions and limited training samples. Reliance on high-quality datasets limits the practical applicability of these methods in real situation, where data may contain noise and missing information.

The motivation for this research arises from the need to develop an automated, robust, and accurate skull damage detection framework that can effectively overcome these limitations. In contrast, traditional machine learning approaches are capable of capturing such features but suffer from limited automation and scalability. Therefore, there is a strong need for a unified approach that combines the strengths of both methodologies.

Based on the analysis of existing literature, several research gaps have been identified. There is an absence of a unified framework that integrates both 3D skull modeling and 2D image-based analysis for damage detection. Moreover, limited attention has been given to hybrid feature extraction strategies that combine deep learning features with handcrafted descriptors. Sequential learning approaches, particularly Long Short-Term Memory (LSTM) networks, remains underexplored in skull damage detection tasks. Additionally, comprehensive evaluation using multiple classifiers to validate model robustness is often lacking. To deal with these issues, this work develops a hybrid approach that integrate CNN-LSTM architecture with handcrafted feature extraction and multiple machine learning classifiers, with the objective of enhancing detection accuracy, system reliability, and automation in skull damage analysis.

3. Methodology

3.1 Framework Design and Overview

The presented methodology introduces a hybrid artificial intelligence–based approach for the automated identification of skull damage by deep learning approaches together with conventional machine learning methods. The designed system incorporates multiple stages, including 3D skull data processing, transformation into 2D representations, extraction of both learned and handcrafted features, and multi-class classification to enhance overall detection performance and reliability.

The general operational flow of the system is presented in Fig. 3.1, comprising key stages such as acquisition of 3D skull models, conversion into 2D images, image enhancement, segmentation for region of interest extraction, feature extraction, and final classification.

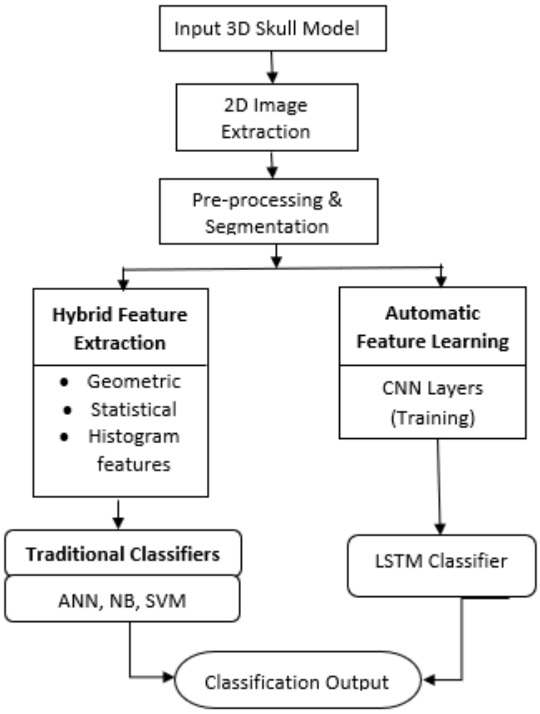

Fig.31 Architecture of the proposed skull damage detection model

3.2 Mathematical Representation of Dataset

Let the input skull dataset be represented as:

$S = \{S_1, S_2, \ldots, S_n\}$

where each S_i represents an individual 3D skull model belonging to either the normal or damaged class.

Each 3D skull model is converted into its corresponding 2D representation using projection techniques:

$$I = f(S)$$

3.3 Pre-processing

The extracted 2D skull images often contain noise, intensity variations, and unwanted artifacts. Pre-processing is therefore carried out to increase feature extraction and image quality.

The pre-processing operation is defined as:

$$I_p = Enhance(I) + Denoise(I)$$

where:

- *Enhance(I):* improves contrast (e.g., adaptive histogram equalization)
- *Denoise(I):* removes noise (e.g., median filtering)

This step ensures better segmentation and improves overall model performance.

3.4 Segmentation and ROI Extraction

To extract the skull region, an Otsu-based thresholding method is applied, which adaptively computes an appropriate threshold value for effective segmentation.

$$T = \arg\max \sigma_b^2(T)$$

where $\sigma_b^2(T)$ is the between-class variance.

The ROI is determined using the following expression:

$ROI = I_P > T$

This step separates the foreground (skull region) from the background, reducing computational complexity and focusing on relevant features.

3.5 Feature Extraction

The proposed method employs a dual feature extraction strategy, combining deep learning-based automatic features and handcrafted features.

(A) CNN-Based Automatic Feature Extraction

The extracted region of interest (ROI) is then processed using CNN layers to learn representative deep features:

$F_{cnn} = CNN(ROI)$

The CNN layers automatically learn spatial and structural patterns such as edges, textures, and fractures.

(B) Handcrafted Feature Extraction

In parallel, handcrafted features are extracted to capture domain-specific characteristics:

$$F_h = [F_{geo}, F_{stat}, F_{hog}]$$

where:

- F_{geo}: geometric features (shape, contours)
- F_{stat}: statistical features (mean, variance, entropy)
- F_{hog}: Histogram of Oriented Gradients (texture features)

Feature Fusion and Normalization

A hybrid feature vector is created by combining the extracted features:

$F = [F_{cnn}, (h)]$

To ensure uniform scaling, normalization is performed using the min–max method:

$$F_n = \frac{F - F_{min}}{F_{max} - F_{min}}$$

This improves classifier performance and avoids bias due to feature magnitude differences.

3.6 Classification

(A) Deep Learning Classification (CNN-LSTM)

The LSTM classifier receives the CNN-extracted features:

$Y = LSTM(F_{cnn})$

By keeping contextual information, the LSTM layer improves classification accuracy while capturing sequential dependencies.

(B) Machine Learning Classification

The normalized hybrid features are classified using conventional classifiers:

$Y_c = Classifier(F_n)$

The final classification is performed using multiple algorithms, namely ANN, SVM, and Naïve Bayes classifiers.

3.7 Final Decision Output

The outputs from both classification approaches are used to determine whether the skull is Normal or Damaged.

The hybrid approach ensures improved robustness, accuracy, and reliability in skull damage detection.

5. Results and Analysis

5.1 Experimental Setup

The proposed skull damage detection framework was evaluated using a dataset of 480 3D skull models, consisting of 125 normal and 355 damaged samples. The 3D skulls were acquired using a laser scanning system and converted into 2D images for further processing.

All simulations were carried out in MATLAB. The proposed method was assessed by benchmarking it against conventional classifiers such as Naïve Bayes, SVM, and ANN. To ensure reliable evaluation, the dataset was separated into three distinct training and testing ratios: 95:5, 85:15, and 75:25. The performance of each approach was assessed using widely accepted evaluation parameters, including precision, specificity, accuracy, F1-score and recall.

Table: 5.1 Performance analysis

Accuracy				
Classifier	NB	SVM	ANN	F_CNN_LSTM
5%	91.83333333	88.16666667	96.88888889	100
15%	88.21538462	83.03846154	95.82608696	100
25%	81.24	80	93.69444444	95
Precision				
Classifier	NB	SVM	ANN	F_CNN_LSTM
5%	86.5	86.16666667	94.88888889	100
15%	86.5	81.03846154	93.82608696	100
25%	82.5	79.97058824	91.69444444	92.85714286
Recall				
Classifier	NB	SVM	ANN	F_CNN_LSTM
5%	90.1	89.9	98.84259259	100
15%	87.1	87.2	97.73550725	100
25%	82.20769231	84.66	95.5150463	100
Specificity				
Classifier	NB	SVM	ANN	F_CNN_LSTM
5%	90.42	93.86666667	95.08547009	100
15%	85.84857143	88.73846154	94.06354515	100
25%	84.58	71.55714286	92.01388889	98.66
F1 Score				
Classifier	NB	SVM	ANN	F_CNN_LSTM
5%	88.26330691	87.99375237	96.82539683	100
15%	86.79896313	84.00640117	95.74090506	100
25%	82.35358677	82.24850646	93.56575964	96.2962963

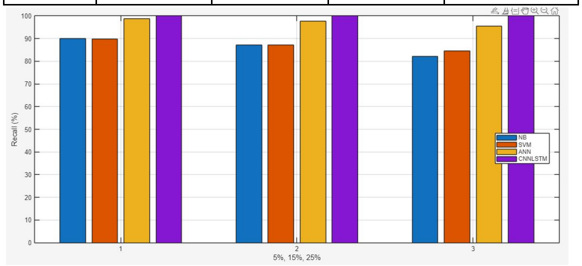

Fig. 5.1 The graphical comparison of classification recall for all models across different training–testing ratios.

It is clear from the graph that: The suggested CNN-LSTM model constantly produces the best results. Traditional models show performance degradation as test data increases. The proposed model maintains robustness even with higher testing data (25%).

The suggested SIDD-CNN-LSTM architecture regularly performs better than conventional machine learning models, according to the comparative study of classifiers, including NB, SVM, and ANN, across multiple evaluation metrics and varying training–testing ratios. The proposed model achieves perfect classification performance for 5% and 15% test splits, and sustains high performance with 95% accuracy under the 25% test condition, indicating strong generalization capability. On the other hand, when test data increases, conventional classifiers perform worse, especially in recall and precision, which causes more incorrect positive and negative classifications. A consistently strong recall performance is observed for the proposed approach ensures reliable detection of damaged skull instances, which is critical in medical diagnostics, while high specificity confirms accurate classification of normal cases. Additionally, the better F1-score validates the durability of the hybrid feature integration technique by reflecting a fair trade-off between precision and recall. The observed improvement arises from the complementary capabilities of CNN for feature representation and LSTM for capturing sequential dependencies, along with the inclusion of handcrafted features, which collectively enhance discriminative capability and classification stability. These results demonstrate the efficacy of the suggested method for precise and automated skull injury identification in biological applications.

5.2 Performance Analysis with other method (Accuracy + Detection Time)

The effectiveness of the proposed SIDD-CNN-LSTM framework is assessed by considering both classification accuracy and computational time. Experimental observations indicate that the model delivers high performance, achieving up to 100% accuracy under lower testing proportions and maintaining approximately 95% accuracy for larger test splits. When compared with previously reported approaches, deep learning techniques, including CNN-based and attention-driven models, typically exhibit accuracy levels ranging from 92% to 99% in fracture detection applications [Paper 23, 27–29]. For example, transfer learning–based CNN approaches have demonstrated an average AUC of 0.96 with accuracy close to 92% [Paper 23], while hybrid frameworks that integrate deep feature extraction with ensemble methods have reported performance levels of up to 99.14% [Paper 29]. Even with these improvements, most methods still focus only 2D medical image analysis and do not effectively combine hybrid feature representations with sequential learning strategies.

From a computational perspective, the proposed framework exhibits an average detection time of 2815 seconds, which is relatively higher compared to lightweight architectures such as MobileNetV2 that are designed for real-time applications [Paper 29]. This increased processing time is mainly due to the multiple stages involved in the pipeline, including transformation from 3D to 2D, image enhancement, region of interest extraction, hybrid feature generation, and CNN-LSTM–based classification. Nevertheless, the proposed method achieves superior accuracy and robustness, making it well-suited for domains such as forensic investigation and biomedical diagnosis, where accuracy is prioritized over execution speed. In contrast to classical machine learning algorithms and standalone deep learning approaches, the hybrid framework demonstrates improved generalization capability and consistent performance across varying data conditions.

Overall, although the proposed system incurs a moderate computational overhead, it provides an effective balance between accuracy and reliability. This characteristic makes it appropriate for offline analysis, clinical decision-support systems, and forensic applications, where high precision is essential.

Conclusion

The present work develops a hybrid AI-based system for automated detection of structural damage in three-dimensional skull models. The developed SIDD-CNN-LSTM approach combines deep learning–based feature learning with handcrafted feature extraction to enhance detection performance and system robustness. The overall pipeline integrates multiple stages, including preprocessing, region of interest extraction, CNN-based representation learning, and LSTM-based classification, along with hybrid feature fusion using structural, geometric, and HOG-based descriptors.

The proposed method was validated on a dataset containing 480 skull samples, comprising both normal and damaged instances. Experimental findings indicate that the model consistently outperforms conventional classifiers such as ANN, SVM, and Naïve Bayes across key performance measures, including precision, specificity, accuracy, F1-score and recall. The use of hybrid feature representations strengthens the model's effectiveness in identifying spatial as well as structural characteristics of skull damage. Furthermore, evaluation under different training–testing configurations demonstrates that the model performs reliably and generalizes well.

The model offers a high degree of diagnostic reliability despite the comparatively longer average detection time, which makes it appropriate for use in clinical decision support systems, biomedical research, and forensic investigation. Overall, the proposed hybrid framework successfully addresses key limitations of existing methods by combining automation with domain-specific feature representation. The future work is to prepare automated frame work to detect not only skull damage but also reconstruction all the damaged skull.

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