Original Article

Bone Fracture Detection Using Morphological and Comparing the Accuracy with Genetic Algorithm

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Abstract

Aim: The purpose of this study is Bone fracture detection using Morphological algorithm and comparing the accuracy with Genetic Algorithm**. Materials And Method:** A total of 32 samples wrist fracture dataset from kaggle. Morphological and Genetic algorithms are used to analyze the Bone fracture with a G-power value of 80 %. **Results:** From the MATLAB simulation, Morphological achieved 87.46 % accuracy rate compared to 83.25 % accuracy rate by Genetic algorithm. The P value is 0.029 in statistical analysis. **Conclusion:** From this case study it is concluded that the image segmentation, Morphological algorithm and Novel feature extraction gives high accuracy compared to the Genetic algorithm based on dataset and morphology developed from Edge detection.

Keywords: Image Segmentation, X-ray, Morphological algorithm, Bone Fracture Detection, Deep Learning, Genetic Algorithm, Novel Feature Extraction.

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INTRODUCTION

The use of X-ray diagnostic imaging in the identification of bone fractures inside the human body is critical. With image segmentation, medical practitioners can make better decisions and manage injuries more effectively. Medical x-ray image processing is used to further examine the recorded digital images in terms of improving diagnosis outcomes. Image morphology can be defined as a theory for analysis of spatial structures in opening and closed images (Kevin Zhou, Greenspan, and Shen 2017). Using morphological technique reduces noise, improves image segmentation, and emphasizes the fracture area. Because of the combined effect of the morphological technique and the canny edge recognition algorithm, the fracture edges are even more vividly exposed (Kalita et al. 2018). Applications of morphological algorithms are Morphological smoothing One way to achieve smoothing is to perform a morphological opening followed by a closing. Smoothing of the morphology Smoothing may be achieved by performing a morphological opening followed by a morphological closure gradient. In the source image segmentation (Bhattacharjee et al. 2020), the morphological gradient reveals strong gray-level changes (Chandra Shekhar Rao and Sammulal 2021).

The existing system has 20,300 conference papers in Google Scholar and 248 IEEE journal papers in the current system. Previously, the majority of pattern object identification was done by deep learning and x-ray image analysis (Bharodiya and Gonsai 2019). This research focuses on identifying whether the iliopectineal line is interrupted, a key condition for automating the acetabular fracture categorization process and providing orthopedic surgeons with computer-assisted diagnosis (Damien et al. 2019). X-ray image enhancement techniques, morphology algorithm to extract features, and scan line algorithm to determine the site of a bone fracture (Muchtar et al. 2018). Because recognising apparent fractures including such open and cracked fractures is straightforward, even for a non-medical observer, the proposed approach focuses on discovering demanding fractures that are easily neglected (Hržić et al. 2019). Several anterior fracture classification systems, along with the Hansen, Jensen, Boyd-Griffin, Kyle, and AO/OTA classifications, have been devised and utilized in clinical practice for decades (Li et al. 2019). The creation and testing of fully automated deep learning techniques that are taught to detect anomalies on non-contrast head CT and X-ray images that require immediate treatment (Chilamkurthy et al. 2018). Nodules recognition, identification, extraction, and noninterpretive tasks are the four areas of deep learning breakthroughs in musculoskeletal radiology (Chea and Mandell 2020)Our team has extensive knowledge and research experience that has translate into high quality publications(Bhansali et al. 2021; Jayanth et al. 2021; Sudhakar, Ravel, and Perumal 2021; Sathiyamoorthi et al. 2021; Deepanraj et al. 2021; Raju et al. 2021; Arun Prakash et al. 2020; Kamath et al. 2020; Shanmugam et al. 2021; Rajasekaran et al. 2020; Adhinarayanan et al. 2020; Rajesh et al. 2020; Aurtherson et al. 2021)

The limitations of the study of existing bone fracture detection is automatically discovered in MATLAB, resulting in a decline in accuracy (Santosh and Hegadi 2019). The goal of this work is to use a morphological algorithm to detect broken bones with a higher readability rate than a genetic algorithm.

MATERIALS AND METHODS

This study work is for the Department of Electronics and Communication Engineering at Saveetha School of Engineering, Chennai. Two groups noise images and image classification for the image from fracture detection, each dataset consists of 16 samples, in total 32 samples with threshold 0.05, 95% confidence and pretest power 80% is taken for test purpose (Ryan 2013).
For Morphological, two processes took the 16 samples from the dataset. The input x-ray image which is collected from the dataset is rescaled into color jpeg (200*180) resolution. By the help of a morphological algorithm (Shivahare 2020) the novel feature extension of the images is processed. These samples are stored in Microsoft Excel for statistical analysis. Morphology is used for sample preparation and the simulation is done in MATLAB. The images are helpful to store the data and these images are labeled on the basis of the folder. By deep learning the data is separated into testing and training sets. The input image of size 200*180 is tuned perfectly for the classification of the datasets by the novel feature extraction, the x-ray images with different sizes cause noise and to reduce this data size will increase and the validation, recognition of the data are done.
Similar to Morphological, the two processes are done for Genetic with 16 samples. the input images from the dataset is rescaled into 24-bit color jpeg (227*227) resolution. The Novel Feature Extraction and the classification of the data is carried out by the Genetic algorithm. The sample values are stored in Microsoft Excel for further statistical analysis. The Factor values of mainly connected layers are increased for the training options in the transferred layers to set the initial rate for fully connected and transferred layers in order to validate the data from the stored database.
The total experiment was done on a Windows platform with dual core processor, resolution of 1024×768 pixels, configuration of 10 th generation, intel i3, 8GB RAM, 1TB HDD, 256 SSD and MATLAB 2018 software with required add-ons for training and testing procedures. The scaling of the image is done at the pre-processing stage and morphologically detects the image, Novel Feature Extraction is done by selecting the factor values and the images are extracted. These factor values have best transferred layers which have greater dimension and this allows for better performance which leads to the successful detection of image. The removal of the artifacts from the dataset images is done in the pre-processing part. The dataset images are collected wrist fractures and leg fractures are marked in deep learning, The preprocess normalization is implemented in the training images and processed using a morphological algorithm for Novel Feature Extraction. These data samples differ from each other and they are like images with dim light, heavy light, etc. The position of these coordinates are tabulated in table-1. The blur images and the images with disturbance are the independent variables and accuracy is the dependent variable in this image recognition system. Independent sample T test is performed and the accuracy of approximate is given in Equation [1] as follow

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN \qquad \text{------------ [1]}$$

Where,
TP - true positive
TF - true negative
FP - false positive
FN - false negative

Statistical Analysis
The software used for this analysis was IBM statistical tools (SPSS) (Jaafar et al. 2020). The Independent-sample t-test is done with the accuracy values of both algorithms. SPSS software is used for statistical analysis(Watkins 2021). Height and Width are independent variables, while accuracy and specificity are dependent variables. The performance of algorithms is compared using an independent t-test.

Result

The input images which are holding for testing and training images with low resolution and noise. Previously the image is read and it undergoes preprocessing technique in which the RGB image is converted into grayscale to reduce the noise (Ali, Abood, and Khudhair 2019). The accuracy differences of these training and testing

images between the morphological and genetic algorithm. Morphological gains the accuracy rate of 87.46 % compared to the existing genetic technique which achieves 83.25 % accuracy rate. The recognition rates of morphological and genetic techniques with different training images on edge detection are represented in Table 1. Table-2 represents the recognition rates of morphological and morphology with different training images to get the values of mean, standard deviation and standard error. The gray variations of test and trained bone images are experimented to evaluate the robustness of morphological and Genetic due to the edge detection on temporary illumination variations in fracture detection. The results of these techniques are presented in Table 3.
The bone image is recognized with the help of bounding box and this image is cropped to increase the accuracy with a resolution of 256*256 (24-bit jpg) bone image. The analyzed bone image and the cropped image based on edge detection is as shown in Fig. 1. Figure 2 shows the accuracy differences of the training dataset between morphological and genetic techniques in deep learning. This shows that morphology achieves a higher accuracy rate of 87.46 % compared to the existing Genetic technique (Marinov, Kalmukov, and Valova 2021).

Discussion

This experiment was done with 39 and 236 training images separately. For 39 training images, the opening values are decreased by 20 % on morphological and morphology does not have a great impact on success rates, but 50 % increase the success rates effectively. Trained sample values taken for statistical analysis using IBM SPSS software. The P value is 0.029 obtained from the SPSS software tool proves that morphology has better accuracy than Genetic in the image recognition system. The comparison of mean accuracy values for two groups morphological and Genetic with p-value 0.05 and error bar 95 % with the effective prediction is shown in Fig. 2. The error bars with the mean accuracy detection +/- 1 SD.
A method for moderately long-bone shaft splitting has been given, as well as fracture diagnosis within the segmented region.With an accuracy of 91.16 %, effectively diagnosed and accurately indicated the sites for tiny, difficult bone fractures in infants responsible for over half and radius bones using local entropy (Hržić et al. 2019). Employing a combined approach of the gradient that incorporates magnitude and direction data, with line parameters derived using a modified Hough transform, to correctly identify fractures within the diaphyseal portion of a long bone with 87.26 % accuracy (Jagtap and Holambe 2018). In the test data set, 83 % of the diaphysis fragmentation borders and 83 % of the fractures inside those features extracted were successfully recognized and detected (Eccles et al. 2020). It is recommended that they complement each other; this may be accomplished by completing a significance and consistency analysis of classifiers, where the best features from the high-dimensional feature collection can be chosen with 82.23 accuracy (Brownlee 2018). The use of deep learning to detect morphological algorithms is viable and can be done with 79.86 % accuracy (Yu et al. 2020). Overall diagnostic accuracy of rib cage reformats for the diagnosis of rib fractures was comparable to those of traditional reformats, with high repeatability and a significant decrease in assessment time 73.46 % accuracy (Urbaneja et al. 2019).
The major limitation of this proposed method is to enhance the image segmentation under different lighting conditions in deep learning. The future scope of this proposed research will be used to improvise the performance rate under different conditions with Novel Feature Extraction.

Conclusion

In this bone fracture detection, a comparative analysis of performance and evaluation of morphological and genetic was trained out using RGB coloured images for image segmentation with Novel Feature Extraction. The results of these experiments show that morphology has increased better in terms of accuracy than Genetic and is less sensitive to the partial blockage.

Declarations

Conflict of interest
No conflict of interest in this manuscript.
Authors Contributions
Author YR was involved in data collection, data analysis and manuscript writing. Author AA was involved in conceptualization, data validation and critical reviews of manuscript.
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Tables And Figures

Table 1. Accuracy obtained for 16 sample images. Mean accuracy 94.59 % for morphological algorithm and 93.61 % for Genetic algorithm

Morphological (Group-1)	Genetic (Group-2)
94.59	93.61
93.25	91.85
92.38	90.34
91.24	88.67
90.56	87.16
89.73	85.63
88.38	83.27
87.53	81.84
86.62	80.58
85.33	79.52
84.72	79.15
84.11	78.71
83.86	78.53
83.34	78.23

82.47	77.74
81.36	77.23

Table 2. Represents group statistics for both sample groups, Mean (87.4669), standard deviation (4.11895 & 5.51614) and standard error mean (1.02974 & 1.37904).

Group Statistics				
Group	N	Mean	Std.Deviation	Std.error
Morphological	16	87.4669	4.11895	1.02974
Genetic	16	83.2538	5.51614	1.37904

Table 3. Represents statistical analysis of independent sample tests for both sample groups. T value (2.448), df value (30 & 27.760) with mean difference 4.21312, significance P-value (0.029)

		Lavene's test for equality of variances		**T-test for Equality of Means**					**95% confidence interval of the difference**	
		F	**Sig**	**t**	**df**	**sig (2 tailed)**	**Mean diff**	**Std. error**	**Lower**	**Upper**
Accuracy	**Equal Variances assumed**	2.27	.029	2.448	30	0.20	4.21312	1.72108	.69822	7.72803
	Equal Variances not assumed			2.448	27.760	0.21	4.21312	1.72108	.68629	7.73996

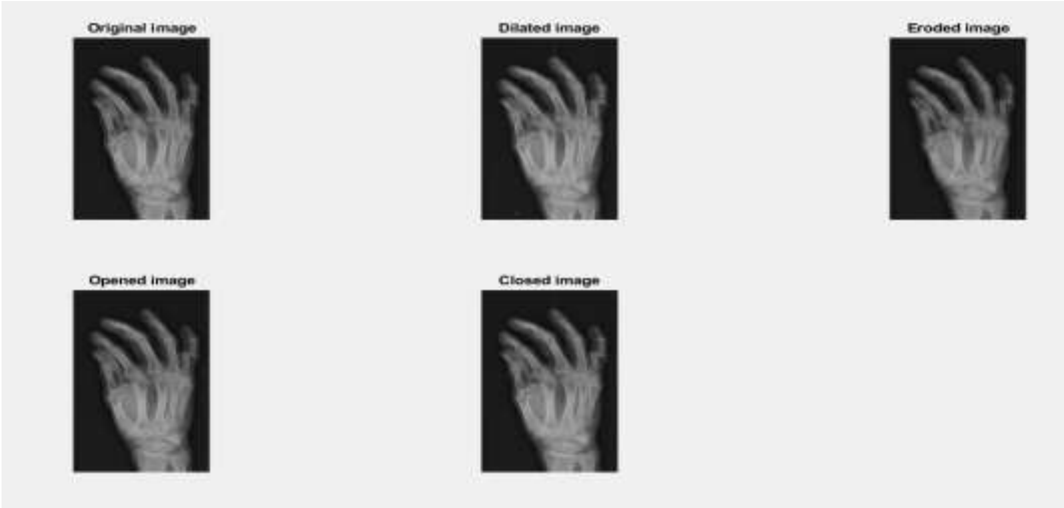

Fig. 1. Represents MATLAB simulation Opened and Closed images obtained by the Morphological algorithm input image with contrast stretched.

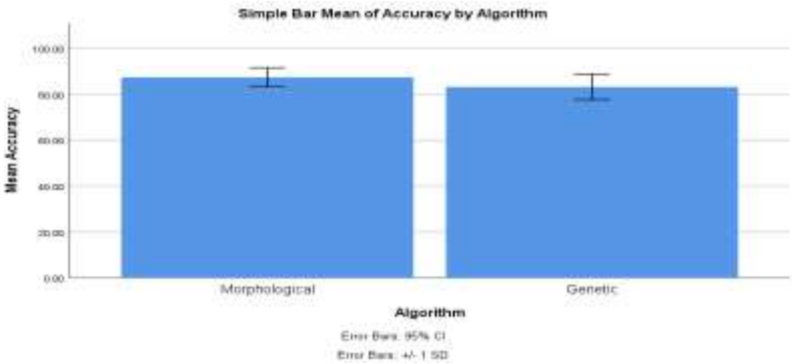

Fig. 2. Comparison analysis of mean accuracy for two groups using Genetic and morphological. morphological shows better accuracy compared with Genetic with error bar 95%, parameter shows statistically significant p-value=0.05. Mean accuracy of detection=+/- 1SD.