International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 10 Issue 6 ǁ 2022 ǁ PP. 1763-1771

Enhanced Grey-Wolf with MSVM Algorithm to Determine the Baa Classification in the X-Ray Images

Tanimulawal Mr.Rehan Khan Mr.YogeshBanyal
M.Tech (cse) student 4th semester
Assistant Professor
Dept. of Computer Sciences and Engineering
AlakhPrakash Goyal Shimla, India

Abstract-*Bone age assessment is also called the skeletal age, which indicates the child's development. It detects metabolic and endocrine disarrangement in the product. The bone age assessment provides better age information from the bones than from the birth date in chronicle age estimation. Usually, the hand and wrist x-ray images are generally taken forthe BAA system. It has been noticed that the X-ray method is more convenient and reliable than other manual methods. Therefore, the proposed work presents a fully automated DL approach for BAA. In this paper, the hand-wrist x-ray images of different categories like 0,1,2,3, etc., are taken as a dataset online. Each image is left-sided people and tagged along with the information of age and gender. Firstly, it will upload the X-ay images and convert them into 2d and 3d formats. The noise distortion has also been removed from the images via filtration, and edge detection has occurred. This stage is followed by feature extraction, which is the most significant step in the process. The GWO method has been implemented and optimized for all the required sets, identifying the bone age. For the training and testing purpose,the improved feature with GWO and MSVM classification model is being trained to access the accuracy of the training and testing phase. The proposed model has achieved maximum accuracy and reduces the error rate values. Simulation outcomes define that the research method attained a difference between manual and predicted BA of about one up to seven years categories, correspondingly, on the Kaggle database. These precisions are similar to state-of-art presentations.*

Keywords-*BAA (Bone Age Assessment), GWO (Grey wolf optimization), Hand wrist X-Ray Images, MSVM classification model.*

Date of Submission: 14-06-2022 Date of acceptance: 29-06-2022

I. INTRODUCTION

In the current years, BAA represents a bone age according to the years as per the growth of bones. It is a standard index used worldwide for medical and non-medical purposes. The study of the bones can be done by taking several bones) to understand the bone age better.The assessment of skeletal development is often performed in the medical field. There are multiple ways toassess bone age; however, the hand wrist x-ray images are perfect for children. The shape, characteristics, and changes of bones play an essential role in biological maturation. Several parameters impact the evaluation of physical maturity during growth. Bone is different from chronological age.

In most cases, the paediatricians and endocrinologists request to get a bone age assessment done to know the actual stature of physical growth in children. There are numerous factors that effects bone age and those factors are genetic and social factors, including gender, nutrition, social factors, chronic diseases, and also endocrine dysfunction. Bone age assessment also helps estimate chronicle age when actual birth data is absent or unavailable in records. It has been noticed that 65percent of all births are not recorded by the age of five years. Therefore, bone age assessment could accurately estimate a child's age in case of applying for any competitive sports, during immigration, etc. [1]. Severaltechniques have been established to calculateBA using distinct skeletal elements and visualization methods. A serious comparison of these techniques is specified below in fig 1.

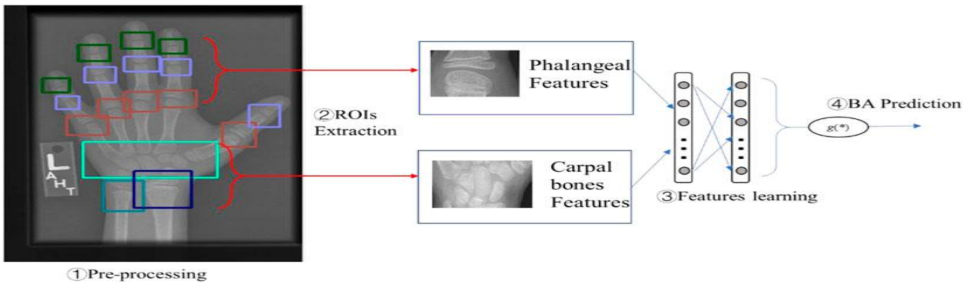


Figure 1.General BAA System [2]

Fig. 1, theplanned BAA system has three different phases. Pre-processing is the initialphase, and Extraction is the second step in the process that includes the exact ROIs used in the clinical method, data processing, feature learning, and fast BAA estimation. These areas are called bounding ROIs. The main techniques of BAA are the GP and TW methods. These methods involve left-hand and wrist radiographs. However, other processes develop BAA methods such as ultrasonographic, electronic, and MR medical imaging techniques. It has been seen that the hand's and wrist's radiographs are the most appropriate for BAA. It is because many bones are possessed by the hands and the wrist, making the evaluation easy. It has been noticed that only the left hand and wrist are being used for the valuation but not the right one. As the right hand is more likely to be damaged and most people are right-handed, these are the significant reasons to use the left hand and wrist. In the early 1900s, it was determined that the left side should be used for any physical measurements at the conferences of physical anthropologists. The hands and bones consist of 19 short bones, ulna, radius, and seven carpals. Out of 19 short bones, 5 are metacarpals, and 14 are phalanges. Bones are formed naturally by endochondral and intramembranous ossification in the ulna,radius, short bones, and carpal bones. However, the carpals are not appropriate for the valuation as there is an early occurrence of maturation in the carpals. BAA has different methods, such as; the GP method, TW3, etc.

- ***GP method*****:**In this method, the assessment of the bones can be assessed by associating the nearest standard radiograph in the atlas and the radiograph of the patient. The GP method is faster and easier to understand and implement. It has more minor errors of prediction. The argument-based study of humansand developmenthas been directed based on a standard hand radiograph. Earlier, the radiographs were obtained between 1931 and 1942. This assessment tested the Cleveland Caucasian children aged 0-19 years, and 100 x-ray images were designated as standard input.As the hand wrist x-ray is most neutral and fast,it offers less radiation exposure to the subject shown in fig 2 (a).

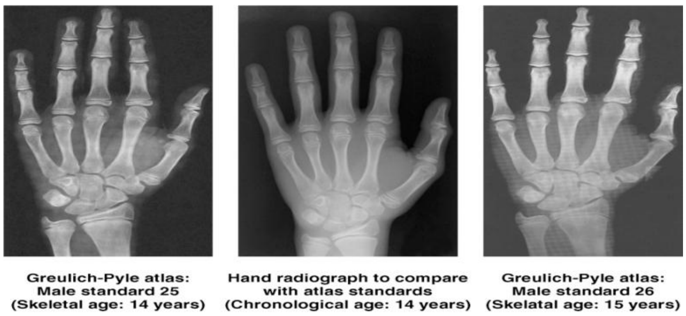


Fig. 2 (a) Different Methods of BAA Clinical Methods [2]

- ***TW method:***There are three types of TW methods for different purposes. The RUS method is used for assessing the 13 long or short bones, and for determining seven carpals and the 20 bones, the carpal technique is used. The TW2 technique is also known as the scoring method. Inthe first step, each bone is characterized into a phase, i.e., from phase A to H or I. Afterward, a total score is calculated only when a score replaces it; that score is the total score that transforms into the bone age. Using radiographs collected in the 1950s and 1960s of different middle-class children in the UK, the TW2 method was developed and shown in fig 2(b). However, this method was created in 2001 to compare and update the relationship between bone age secular trends and total bone maturity score.The latest version TW method called as TW3 method. Now there are more updated parameters and indicators in the TW3 technique, making it easy to attain improved accuracy of bone age assessment.

Fig 2 (b) TW3 methods divides the hand-wrist bones into two series[2]

- ***Ultrasonographic method:*** The ultrasonic method *uses* two transducers. One of these transducers creates ultrasonic waves with anincidence of 750 kHz; other transducers act as receivers. That receiver transducer receives the waves that the other transducer transmits at the end of the radius and ulna. There is an ultrasound device named Bone Age that calculates bone age. It is connected to a central unit. This method is less time-consuming as it takes only five minutes to provide an accurate result. While processing, 11 cycles of dimension are finished. In the end, the processdatafrom the patient's demographics, the results of the ultrasound, and skeletal age can be computed. However, ultrasound can calculate the initial stages of bone age; therefore, it requires further execution in other ways. Large sample size in a multiethnic population is necessary if the wrist radiographs need to be replaced.

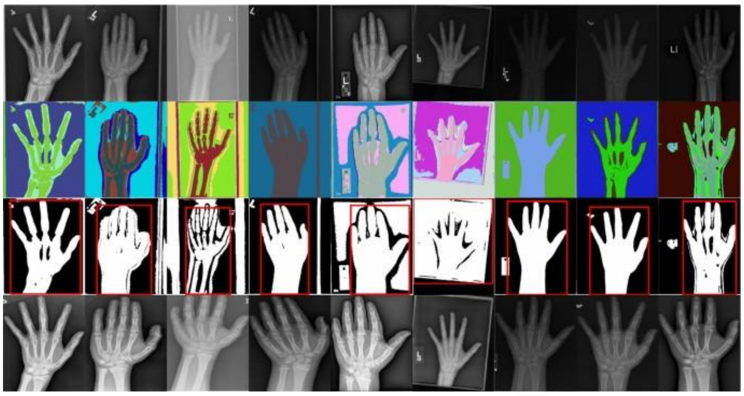


Fig. 3Ultrasonic x-ray images [3]

- ***Computerized Method:***Several automated methods are based on the TW method for boneage assessment. For example,in computer-assisted skeletal age score i.e., CASAS, various mathematical coefficients are used to represent and digitize an image in this method. Each stage of TW standards compares these coefficients with the generated images to determine the closest match. It has been observed that the manual methods are less reliable than the CASAS. The only limitation of the CASAS is that each must be located manually. Therefore, it is more time-consuming than the manual methods[4].

BAA has various advantages and applications; (i) The use of learning techniques that can automate the whole bone age assessment, making it valuable andless time-consuming.(ii) The methods had been used for the research ismore straightforward and reliable for the overall performance of the system. (iii)The outcome has been the most accurate for assessing bone age.

X-ray images verified the presence and alteration in the above procedures. The decision about the age with no-doubt depends on the verification of the timing of the advent of ossification centres and EFI (epiphyseal fusion identification)[5], which is reliant on whether the DB is being detected or whether it is being imagined by an IA (imaging approach) like X-ray or radiograph. The main issues discussed are as follows: (i) Maximum time consumption (ii) More Expensive (iii) Classification issues in the MID (medical image domain), and (iv) Interferences presents an X-ray image quality degradation and error rate increase [6].

The main proposed work of the objective of the research technique is to improve the process of assessment and detection of the bone hand x-ray images. The grey wolf with the MSVM classification method has improved the RMSE and MAE rates. Generally, it has utilized ML (machine learning) concepts following training and testing.

The following sections are; section 2 describes the analysis of the existing methods. It includes the definition, its processes, an explanation of how it works, advantages, and gap/problem. Section 3 discusses the proposed methodology and results in analysis in section 4. Section 5 includes the conclusion and future scope.

II. RELATED WORKS

BAAexplains how fast and slowly a human's skeleton matures from their hands and wrists' X-ray appearances. The doctors can diagnose conditions that how rapidly physical growth is happening in a body through this assessment. It is constructive in prediction of various growth disorders. It generally suggested by paediatricians or paediatric endocrinologists. **Poojary, N. B., et.,al(2021)[7]** presented theory did transfer learning with the Exception architecture. The customized training was performed on the pre-trained convolution neural network. The researchers used 12811 male and female bone images from the Kaggle RNSA bone age dataset. The attained value of MAE was 8.175 months in both genders and also, it aligned with the initial MAE value in under a year. It had been noticed that the accurate prediction value of bone age of an individual could be taken from the bones found in the centre of hands and wrist. **Shastry, A. S., et.,al(2021)[8]**In this paper, the researchers used architecture called Exception and a dataset of left-hand radiographs provided by RSNA. With the help of this architecture, the old and standard convolution operation was replaced by a much more efficient operation that made the whole process less time-consuming. The new operation named Depth wise Separable Convolution was trained on an enormous dataset. Two activation functions, ReLu and Swish, were used for the demonstration. The demonstration was done on the accuracy of the model. The result indicated that the MAE was 0.183 years compared to the MAE of 0.2414 years that too given by the ReLu, which also showed that ReLu outperformed well in deeper convolution. **Booz, C., et. al(2020)[9]** proposed a theory to examine the correctness and productivity of novel AI software versions for bone age assessment. It compared the automated BAA and Greulichpyle method. A dataset of radiographs of 514 patients was taken and analyzed in the retrospective study. The total evaluation of bone age was carriedout independently and AI and Greulichpyle method was applied to each set. There was no statistical difference between correlation analysis and reader agreement; however, using the AI reduced mean reading times by 87%. Therefore, in the presented research, the novel AI software provided higher accuracy in automated BA assessment. **Son, S. J., et.al(2019)[10]** described a Tanner- Whitehouse (TW3) based fully automated BAA system using deep neural networks. The researchers extracted 13 ROIs and addressed the challenges in the whole research. A customized deep neural network was used to learn local discriminative features within small greyscale ROI images. The dataset of approximately 3,300 X-ray images was used to measure the proposed work's Root Mean Square Error and Mean Absolute Error. The accuracies of the skeletal maturity levels based on 13 ROIs were 79.6% for top 1 and 97.2% for top 2 predictions. However, the improved result came out with a few particular modifications to CNNs and other stages of the procedure.**Liu, X., et.,al(2019)[11] s**uggested a novel approach to detect automatic bone age assessment by using TW3. X-ray images were used as a dataset containing 1,100 hand bone images explained manually with ROI extraction, classification, and BAA. The explained theory achieved 0.2685 MAE by integrating CNNs with TW3-RUS BAA system,which provided the best result. DeepTW3 performed accurately and also offered an interpretation ofthe results. The suggested theory stated that a more precise localization of bones was seen by utilizing the key point detection model. However, the existing object detection method could not provide expecting accuracy. **Wibisono, A., et.,al(2019)[12]** suggested two automatic bone age assessment approaches. One approach is classic machine learning, and the other is deep learning.

Further, two different pre-trained models were utilized for a deep learning approach, and those models were VGG16 and MobileNets. Several traditional regression algorithms and the features of the images had been extracted by canny edge detection implemented by classic machine learning. However, the result showed that the deep learning-based VGG16 model performed better and achieved 14.78 months MAE and 18.93 months RMSE. On the other hand, a better error percentage i.e, 28.34% had been noticed via the classic machine learning approach as time execution was way faster thanthe traditional machine learning approach. Table 1 describesBAA's proposed methods, problems, tools, and performance analyses.

Table 1: Comparative Analysis

Author Names	Proposed Method	Dataset	Parameters
Poojary, et al. (2021) [7]	CNN AHE method Xception Architecture	Kaggle RNSA Bone age x-ray images	MAE Accuracy
Shastry, et al. (2021, September). [8]	CNN	RNSA Dataset	MAE
Booz, C., et al. (2020)[9]	GP method	Dicom images	MAD
Son, S et al. (2019)[10]	CNN GP and TW3 method	Publicly dataset	Prediction accuracy Inference Time
Liu, X., et al. (2019, November)[11]	Deep-TW3 method CNN RSU ROI	X-ray images	MAE
Wibisono, et al.. (2019, July)[12]	Pre-train CNN Vgg16 and MobileNet	RNSA dataset	MAE RMSE SMAPE

Abbreviations: CNN (convolutional neural network); TL (transfer learning); AHE (Adaptive Histogram equalization); MAE (mean absolute error); GP (greulich-pyle) method; AI (artificial intelligence); MAD (mean absolute deviation); TW3 (Tanner and Whitehouse);RUS (radius, ulna and short bones);ROI (region-of-interest); RMSE (root mean square error); SMAPE (Symmetric Mean Absolute Percentage Error).

III. RESEARCH METHODOLOGY

The main motive of the objectives of the research technique is to improve the process of assessment and detection of the bone hand x-ray images. The grey wolf with the MSVM classification method has improved the RMSE and MAE rates. Generally, it will utilize ML (machine learning) concepts following training and testing steps.

The proposed flow chart steps are described below:

- Hand x-ray image acquisition
- Hand x-ray conversion (2D to 3D) image
- To check the distorted image and apply the filtration method to check the noise from the uploaded image.
- Feature Extraction procedure using KPCA method.
- Feature selection process using GWO optimization method.
- Assessment using MSVM classification method
- It calculates the research system performance metrics such as MAE, RMSE, etc.
- After the evaluation process, it has compared performance metrics with other parameters such as MAE, RMSE, etc.

This research work explores the database from the online KAGGLE site. The database is a gathering of hand-wrist x-ray images of different categories like 0,1,2,3, etc.

- The proposed work will upload the image and convert the 3d to 2d format. It optimized the hand-wrist x-ray image dimensional size of the uploaded effort image. It identifies the noise in the altered x-ray images.
- The filtration process will remove the faint noises in the x-ray images. After the filtration process, we will find the un-defined noises and apply the edge detection method to detect the edges.
- FE (feature-extraction) procedure will propose in this work. This procedure is the most significant concept and extracts reliable feature vectors.
- The feature selection process will implement the GWO method. This method has optimized all required feature sets and identified the age of the bone x-ray images. After this, it will execute the MSVM classification method. The training, testing, and validation database comprises various phases. The training feature sets that can be used to train the classification model and test feature sets are utilized to assess the accuracy of the train and test phase. The BA with MAE and RMSE values will calculate and compare the research model performance metrics with existing methods.

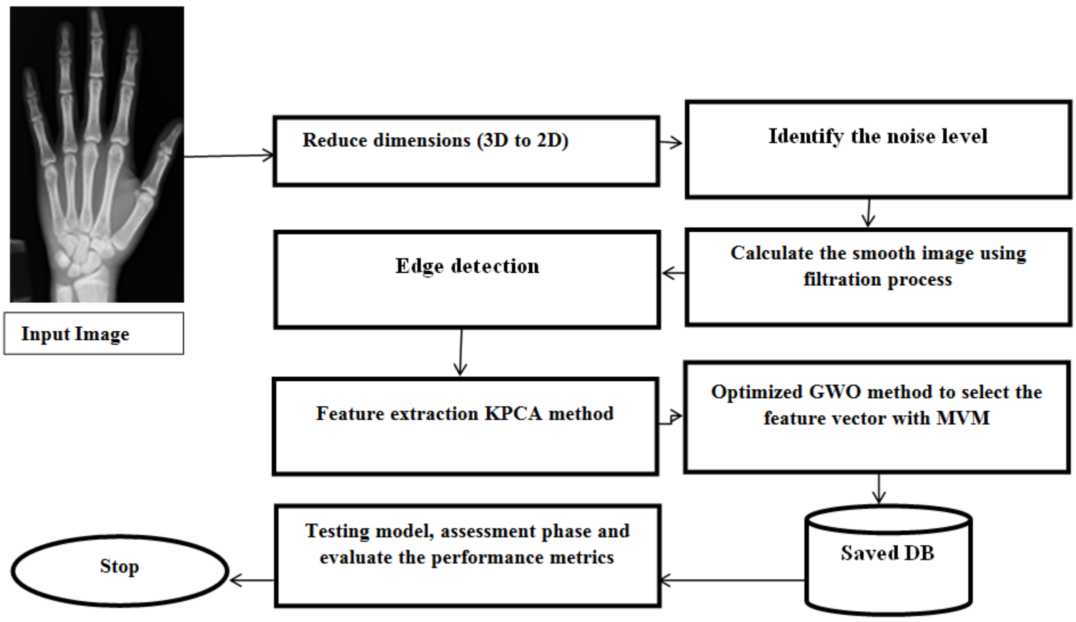


Fig. 4 Proposed FlowChart

IV. RESULT AND DISCUSSION

This section describes the proposed result discussion and UsesMatlab as a stimulation tool in the bone age assessment. MATLAB can perform various functions, including matrix manipulations, program development, information visualization, and feature charting, and communicate with programs written by many other programmers. The proposed model has used performance metrics such as recall, precision, accuracy, and MAE. The proposed work has used RSNA 2017 [13] dataset. There was a contest to accurately verify the child's age from an x-ray of their hand images. It is the dataset on KAGGLE, creating it simple to simulate and do informative demos. Generally, it may be there are some novel ideas for constructing more innovative models for managing x-ray images

4.1 Mathematical Analysis

- ***MAE:***The magnitude of change between the remark's prediction and that remark's actual value. It takes the average of absolute errors for a group of forecasts and statements as a dimension of the magnitude of mistakes for the whole group.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|X_i - X \quad | \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(i)}$$

- ***RMSE***is the square root of the MSE of all the errors. RMSE is widespread and is considered an excellent general-purpose error metric for numerical predictions.

$$RMSE = \sqrt{\sum_{j=1}^{m}\frac{(yi' - yi)^2}{m}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \text{(ii)}$$

- ***The accuracy rate*** is the fraction of correct forecasts for a given database. When it has anML model with an accuracy rate of 85%, statistically, we expect to have 85 correct one out of every 100 calculations.

$$Accuracy = \frac{tp+tn}{tp+tn+fp+fn} \ \ldots\ldots\ldots\ldots\ldots\ldots. \text{(iii)}$$

- ***Precision*** is one pointer of the ML model's performance – the excellence of an optimistic prediction made by the model. It refers to the number of TPs divided by the total number of optimistic predictions.

$$Precision = \frac{tp}{tp+fp} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(iv)}$$

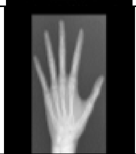
- ***A recall*** is calculated as the ratio between the numbers of positive samples correctly classified as favorable to the total number of actualexamples. The recall measures the model's ability to detect positive samples. The higher the recall, the more positive samples detected.

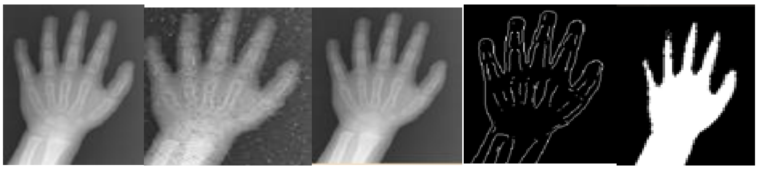
$$Recall = \frac{tp}{tp+fn} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(v)}$$

4.2 Results Analysis

Using improved Features with GWO and MSVM Classification Model as our proposed model in the BAA classification method and able to attain the MAE, RMSE, Accuracy, Precision, and Recall on training and testing set. The proposed model has been able to produce outcomes comparable to the recent state-of-the-art technique of automated BAA.

Table 2. Assessment of BAA system

Bone X-Ray Images	Age-based on chronological	Model assessment accuracy
	7 years	98.0
	5 years	98.2
	4 years	98.6
	3 years	98.67



(i) (ii) (iii) (iv) (v)

Fig. 5 (i) input Image (ii) Noise Image (iii) Filter Image (iv) Edge Image (v) Segmented Image

Figure 5(i) uploads the input image from the train dataset folder. Fig 5(ii) defines the identity of the salt and pepper noise in the uploaded X-ray image. It represents a smooth X-ray image. Fig (iii) It applied the MF (median filter) method to remove the noise and noise in the actual print. The MF method implemented the noise X-ray image; it converts the noise image after the filtration procedure to create a 2D transformation. After filtration,in Fig 5(iv), the edge detection is verified by the single incentive in the sifted image. It executed the Sobel operator of the image and used it as a piece of the image get ready. PC vision, especially inside the edge area, counts where it makes an image focusing on edges. Fig 5(v) defines the segmentation developed by the OSTU technique. This method converts the uploaded image to a grey threshold value and BI (binary image).

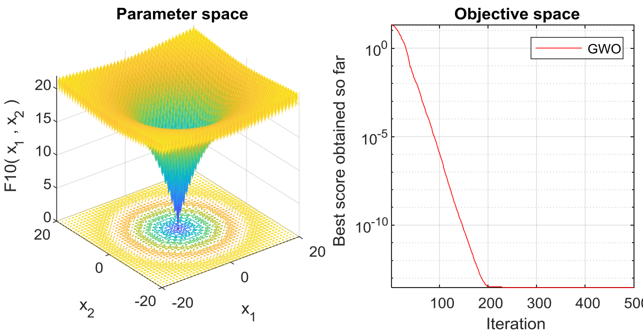


Fig. 6(i) Feature Extraction Process and (ii) Optimized feature vector

Fig 6 (i) defines that the kernel principal component analysis calculates the unique properties. In this feature, data divide into two features Eigen values and Eigen vectors. We implement the feature extraction technique using the KPCA algorithm. A method for investigation comprises the direct mix of preparation of factors with the most significant variation and expelling its impact, progressively rehashing this. KPCA permits the evacuation of the second-arrange connection among given arbitrary procedures. By registering the eigenvectors of the covariance framework of the information vector, KPCA straight changes over a high-dimensional info vector into a low-dimensional one whose segments are uncorrelated.Fig 6(ii) defines the optimized feature vector using the GWO optimization technique. This graph represents the parameter space and objective space w.r.t number of iterations. When the number of repetitions increases, the objective space or the optimized feature vector is reduced compared to the extracted feature vector.

Table 3: Proposed Parameters

Parameters	**Values**
MAE	**3.11**
RMSE	**3.113**
Accuracy (%)	**98.0**
Precision (%)	**96.85**
Recall(%)	**96.84**

Table 3 defines the proposed parameters: accuracy is 98.0 per cent, precision value 96.85 per cent, recall value 96.84. The RMSE and MAE error values are 3.113 and 3.11. The proposed model has improved the accuracy, precision, and recall rates and reduced the error rate such as RMSE and MAE.

Table 4. Comparison

Parameters	**Proposed Work (KO-MSVM)**	**Existing Method (CNN)**
MAE	3.11	6.7
RMSE	3.113	11.4

Table 4 shows the comparative analysis with the proposed improved Kernel-Optimizer MSVM method and the existing CNN model. The proposed Kernel-optimizer MSVM Classifier model has optimized the error rates compared to the current model. The proposed model has achieved a 3.11 MAE value, and the RMSE value is 3.113 compared to the existing method.

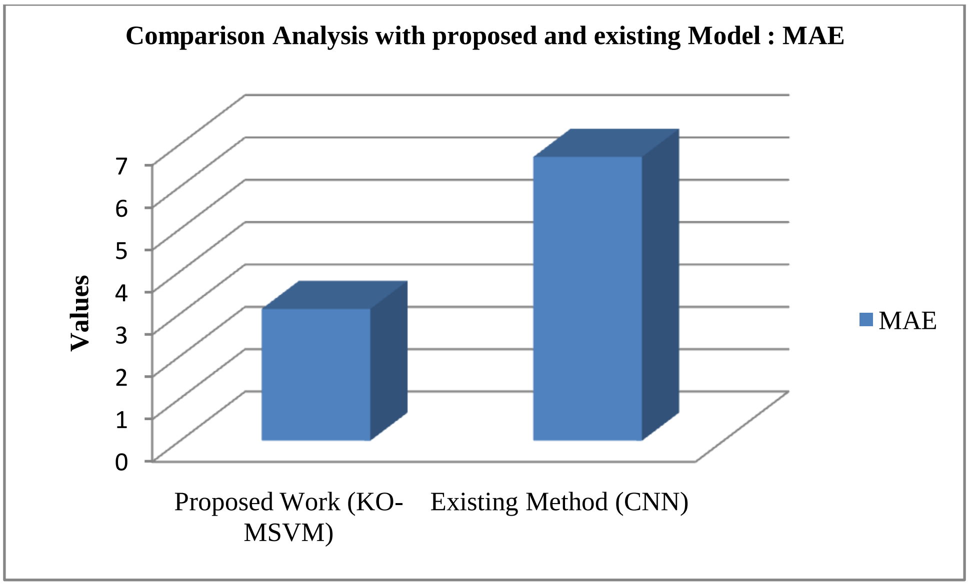


Fig. 7 Comparison: MAE with KO-MSVM and CNN models

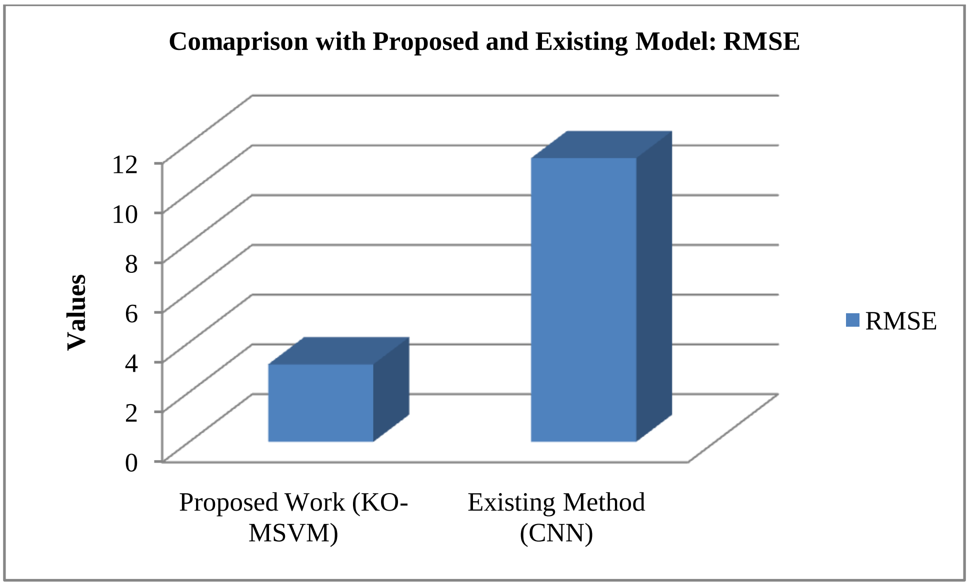


Fig. 8 Comparison: RMSE with KO-MSVM and CNN models

Figs 7 and 8 define the comparative performance analysis with the proposed KO-MSVM and CNN existing models. It has a rapid learning speed, but it is performed at an improved accuracy rate; moreover, it expensive several iteration evaluations and learning feature sets of complete radiography without ROI or KPCA feature extraction. Compared with these two models, the research method might attain good performance with a relatively minimum cost since it optimizes feature sets' evaluation complexity in only various classification and DL models. So, briefing the outcome above, it is concluded that the research model might realize both efficient and effective in developing a better bone age assessment system for business needs. The proposed method has optimized the MAE and RMSE error rates compared to the existing model.

V. Conclusion and Future Work

The proposed work realizes rapid, valid feature extraction and classification for bone age assessment analysis, depending on the improved KO-MSVM method, this research work an improved ML models. Initially, faced with actual hand-wrist radiographs, this article overviewed various requirements of x-ray image pre-processing phases, like edge detection, noise removal, segmentation, feature extraction, and improved classification model. Feature extraction and selection processes are mainly measured in this article for BAA analysis. Then, extracted features are optimized uniformly, and input to extracted features with GWO and classification using the MSVM model is built to classify the BA rapidly. Simulation depends on the data from the RSNA x-ray image dataset implemented. The comparison analysis has done with an improved KO-MSVM and CNN classification model with MAE and RSME parameters. The implementation system may be developed on a computer with a single GPU in the clinical environment. The BAA research model, which comprises hand-wrist x-ray image segmentation, feature extraction, selection, and classification modules, should be validated on other MIP (medical image processing) issues.

References

[1]. Cavallo, F., Mohn, A., Chiarelli, F., &Giannini, C. (2021). Evaluation of Bone Age in Children: A Mini-Review. *Frontiers in Pediatrics*, *9*, 21.

[2]. Guo, L., Wang, J., Teng, J., & Chen, T. Bone Age Assessment Based on Deep Convolutional Features and Fast Extreme Learning Machine Algorithm. *Frontiers in Energy Research*, 888.

[3]. Mughal, A. M., Hassan, N., & Ahmed, A. (2014). Bone age assessment methods: a critical review. *Pakistan journal of medical sciences*, *30*(1), 211.

[4]. Li, S., Liu, B., Li, S., Zhu, X., Yan, Y., & Zhang, D. (2021). A deep learning-based computer-aided diagnosis method of X-ray images for bone age assessment. *Complex & Intelligent Systems*, 1-11.

[5]. Son, Sung Joon, Youngmin Song, Namgi Kim, Younghae Do, NojunKwak, Mu Sook Lee, and Byoung-Dai Lee. "TW3-based fully automated bone age assessment system using deep neural networks." *IEEE Access* 7 (2019): 33346-33358.

[6]. Lee, Hyunkwang, ShaheinTajmir, Jenny Lee, Maurice Zissen, Bethel AyeleYeshiwas, Tarik K. Alkasab, Garry Choy, and Synho Do. "Fully automated deep learning system for bone age assessment." *Journal of digital imaging* 30, no. 4 (2017): 427-441.

[7]. Poojary, N. B., Pokhare, P. G., Poojary, P. P., Raghavani, C. D., &Khanapuri, J. A Novel Approach for Bone Age Assessment using Deep Learning.(2021)

[8]. Shastry, A. S., Mervyn, B. A., Rizvi, B. Z., Menon, V., &Girisha, G. S. (2021, September). Automatic Bone Age Assessment of Radiographs using Deep Learning. In *2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)* (pp. 1-7).IEEE.

[9]. Booz, C., Yel, I., Wichmann, J. L., Boettger, S., Al Kamali, A., Albrecht, M. H., ...&Bodelle, B. (2020). Artificial intelligence in bone age assessment: accuracy and efficiency of a novel fully automated algorithm compared to the Greulich-Pyle method. *European radiology experimental*, *4*(1), 1-8.(2020)

[10]. Son, S. J., Song, Y., Kim, N., Do, Y., Kwak, N., Lee, M. S., & Lee, B. D. (2019). TW3-based fully automated bone age assessment system using deep neural networks. *IEEE Access*, *7*, 33346-33358.

[11]. Liu, X., Wang, G., Xu, Y., Chen, N., & Chen, T. (2019, November). Bone age assessment by deep convolutional neural networks combined with clinical TW3-RUS. In *2019 IEEE international conference on bioinformatics and biomedicine (BIBM)* (pp. 948-952).IEEE.

[12]. Wibisono, A., Saputri, M. S., Mursanto, P., Rachmad, J., Yudasubrata, A. T. W., Rizki, F., & Anderson, E. (2019, July). Deep learning and classic machine learning approach for automatic bone age assessment. In *2019 4th Asia-Pacific Conference on Intelligent Robot Systems (ACIRS)* (pp. 235-240).IEEE.

[13]. https://www.kaggle.com/datasets/kmader/rsna-bone-age/code.