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Improving Accuracy for Bone Age Prediction from X-Ray Image using Convolutional Neural Network Technique over K-Nearest Neighbors

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Abstract

Aim: To enhance accuracy in predicting bone age from x-ray image to that of Chronological ages using Novel Convolutional Neural Network technique in comparison with K-Nearest Neighbor. **Materials and methods:** Classification is performed by a convolutional neural network (N=10) Over a Support Vector Machine (N=10). The sample size is calculated using Gpower with pretest power 0.8 as an alpha 0.005 **Result:** Mean accuracy Convolutional Neural Network (82.36%) is high compared to K-Nearest Neighbor (70.26%). The significance value for accuracy and loss is 0.389 (p>0.05) **Conclusion:** The mean accuracy of the college recommendation system in Convolutional Neural Networks is better than the K-Nearest Neighbor.

Keywords

Novel Convolutional Neural Network, K-Nearest Neighbors, Accuracy, Prediction, Bone age, Radiology, Chronological.

INTRODUCTION

The skeletal and biological maturity of a person is decided by a child's age. The foremost widely used clinical procedures for Bone age Assessment (BAA) support a visible analysis of individual bone ossification in radiographs of the paw and carpus and a comparison to a regular hand atlas (Kaya 2020) (Mendez-Ferrer 2019). supported the discrepancy between the reading of the age and therefore the age, physicians will create additional correct identification of abnormal development in youngsters (K. S. Lee and Hong 2010; Oecd and OECD 2020). Presently the paw X-ray image is widely used for assessing age because it will render the delicate bone/cartilage development pattern with minimum radiation exposure (Ilyasova, Yu. Ilyasova, and Kupriyanov 2014; Aichinger et al. 2012). Although x-ray radiographs are widely offered in several clinical sites, the reading of the age is non-trivial in radiology. Age prediction mistreatment x-ray pictures is a vital application. A number of the applications of age prediction are the studies that help doctors estimate the maturity of a child's system. Similar applications of age

Assessment are authorized with Deep Learning, Fully machine-driven age Assessment. Nowadays bone age prediction is applied in cybercrime departments, diagnosis of orthopedic related problems. (S. Lee et al. 2022).

In the above analysis, age Prediction from X-Ray Image victimization Convolutional Neural Network Technique around 80 Articles in Google Scholar Science direct and 40 in Scopus (Gilsanz and Ratib 2011). Assessment of a child's skeletal maturity is vital for the management of skeletal disorder throughout growth. Variations between skeletal age and written account Radiation exposure (Sebrechts 2016). Thus Bone Age Assessment is a vital tool within the observation of growth, and to diagnose and manage a large number of endocrine disorders and medicine syndromes age has conjointly been used Radiation exposure for computing the last word adult height children|of children} in ancient healthy kids and may well be utilized in determinant age wherever birth records do not appear to be accessible (Hochberg 2002). The collected knowledge is compared against the taken dataset of Convolutional Neural Network. age classification victimization convolutional neural networks (CNN) as a support tool for connected disciplines in age identification in Radiation exposure (Gaskin et al. 2011). Though different kinds of study for age analysis victimization CNN are conducted, the eye mechanism has not been completely compared to standardized atlas assortment of hand radiography for age assessment Radiation exposure. The regressor network that is employed to predict the age has used three-layer residual dissociable convolution units to provide a deep network, however, maintains an appropriate model size, which is around 20,000,000 parameters. The network has conjointly been trained victimization variable learning rates wherever its worth is linearly decreasing concerning the coaching epoch (Sornay-Rendu et al. 2022).

Previously our team has a rich experience in working on various research projects across multiple disciplines (Venu and Appavu 2021; Gudipaneni et al. 2020; Sivasamy, Venugopal, and Espinoza-González 2020; Sathish et al. 2020; Reddy et al. 2020; Sathish and Karthick 2020; Benin et al. 2020; Nalini, Selvaraj, and Kumar 2020).The existing system of bone age prediction has the unborn selection algorithm that can use the training speed for the model. The pretension is to develop a machine literacy usage that takes into knowledge the varicolored factors in the unearthing and prophecy in real-time. Ultimately a paper is proposed assuming all the limitations. This paper solely focuses on the unearthing and prophecy to increase the rigorousness in unearthing and prophecy of bone age in x-ray images(Ilyasova, Yu. Ilyasova, and Kupriyanov 2014; Aichinger et al. 2012). The purpose of this study is to apply cutting-edge convolutional neural networks to predict and detect bone age automatically, hence improving performance and decreasing the rate of incorrect predictions.

MATERIALS AND METHODS

This study setting was done in the Data Analytics Lab, Department of Information Technology, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences. The sample size taken for this research work is 20 (Group 1=10, Group 2=10). In the prediction of the bone age from an x-ray image, to modify the problem of low accuracy rate convolutional neural network and K-Nearest Neighbor is used. Convolutional neural networks learn about the age of the bone approximately. The K-Nearest Neighbor enables a thorough exploration of bone age data present. The mean accuracy of convolutional neural networks is 82.36%. The mean accuracy of the K-Nearest Neighbor is 70.26%. Dataset for this instance is collected from (https://www.kaggle.com/saksham219/bone-age-prediction-through-x-rays/data?select=bondage-training-dataset) website with 12,611 instances (Safiri and Ayubi 2017).

Novel Convolutional Neural Networks (CNNs, or ConvNets) are a type of artificial neural network used to evaluate visual information. Based on the shared-weight architecture of the Convolution Kernels or filters that slide along input features and give translation equivariant responses known as feature maps as explained in Fig. 1.

Surprisingly, most Novel Convolutional Neural Networks are only equivariant under translation, rather than invariant. They are used in image and video recognition system, recommender systems, image classification, image segmentation, medical image analysis, and natural language processing, among other things.

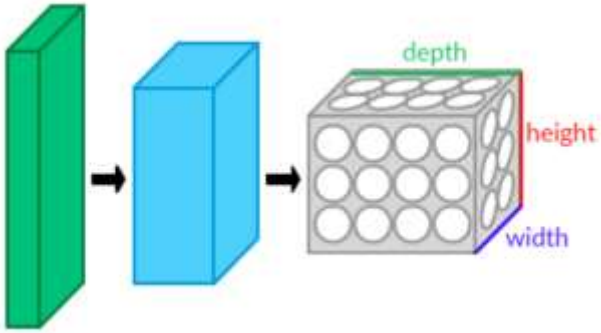

Fig. 1. Novel Convolutional Neural Networks

The input to a CNN is a tensor with the following shape: (number of inputs) x (input height) x (input width) x (number of outputs) x (number of outputs) x (number of outputs) x (number of outputs) x (number of outputs) x (number of output (input channels). The image is abstracted to a feature map, also known as an activation map, after passing through a convolutional layer, with the following shape: (number of inputs) x (feature map height) x (feature map width) x (feature map height) x (feature map width) x (number of inputs) x (number of inputs) x (number of inputs) x (number of inputs) x (number of input (feature map channels). The input is convolved by convolutional layers, which then pass the result on to the next layer. A cell in the visual brain comparably responds to a given stimulus. Each Convolutional Neural only processes data for the receptive field in which it is located. Although fully linked Feed Forward Neural Networks can be used to learn features and categorize data, there are several limitations. Pseudocode for Novel Convolutional Neural Network described in Table 1.

K-Nearest Neighbor is one in all the only Machine Learning algorithms supported by Supervised Learning Techniques. The k-NN algorithmic program assumes the similarity between the new case/data and obtainable cases and places the new case into the class that's mostly the same as the obtainable classes. The K-NN algorithm program stores all the obtainable information and classifies a brand new datum supporting the similarity. This implies once new information seems then it is simply classified into a well-suited class by mistreatment K- NN algorithmic program. K-NN algorithmic program is used for Regression yet as for Classification however principally it's used for Classification issues. K-NN may be a non-parametric algorithmic program, which implies it doesn't create any assumption on underlying information. It is additionally known as a lazy learner algorithmic program as a result, it doesn't learn from the coaching set straightaway instead it stores the dataset and at the time of classification, it performs AN action on the dataset. The KNN algorithm program at the coaching part simply stores the information set and once it gets new data, then it classifies that information into a class that's abundant the same as the new information. Thus for this identification, the KNN algorithm is used because it works on a similarity live. Pseudocode for K-Nearest Neighbors described in Table 2.

Statistical Analysis

The analysis was done by IBM SPSS version 26. In SPSS, datasets are prepared using 10 as a sample size for both the algorithm convolutional neural network and K-Nearest Neighbor. Group is given as 1 for Convolutional Neural Network and 2 for K-Nearest Neighbor, group id is given as a grouping variable, and accuracy is given as a testing variable. An independent sample T-test was conducted for accuracy. Standard deviation, Standard Mean Errors were also calculated using the SPSS Software tool. The significance values of proposed and existing algorithms contain group statistical values of proposed and existing algorithms.

RESULTS

In statistical tools, the total sample size used is 20. This data is used for the analysis of convolutional neural networks and K-Nearest Neighbor. Statistical Data Analysis is done for both the prescribed algorithms namely convolutional neural networks and K-Nearest Neighbor. The group and accuracy values are being calculated for given filtering systems. These 20 data samples used for each algorithm along with their loss are also used to calculate statistical values that can be used for comparison. Table 3, shows that group, accuracy, and loss values for two algorithms convolutional neural network and K-Nearest Neighbor are denoted. The Group statistics table shows the number of samples that are collected. Mean and the Standard Deviation is obtained and accuracies are calculated and entered.

Table 4, shows group statistics values along with mean, standard deviation and standard error mean for the two algorithms are also specified. Independent sample T-test is applied for data set fixing confidence interval as 95%. Table 5 shows independent t sample tests for algorithms. The comparative accuracy analysis, mean of loss between the two algorithms are specified. Figure 2, shows the comparison of the mean of accuracy and Mean loss between the Convolutional Neural Network and the K-Nearest Neighbor.

DISCUSSION

From the results of this study, Convolutional Neural Networks are proved to be having better accuracy than the K-Nearest Neighbor. Convolutional Neural Network has an accuracy of 82.36% whereas K-Nearest Neighbor has an accuracy of 70.26%. The group statistical analysis on the two groups shows that Convolutional neural networks (group 1) have more mean accuracy than K-Nearest Neighbor (group 2) and the standard error mean including standard deviation mean is slightly less than Convolutional neural networks.

This research increases prediction for recognition systems to find better bone age prediction using x-ray images under their data. This model has a slow processing rate with better accuracy (Rajvanshi and Dhaka 2016; Prateek et al. 2019). The slow processing rate is due to the usage of a large database but in the case of a smaller database, both the processing and accuracy are faster and better. The above problem's complexity will be reduced once a model is built (Moolayil 2018). Despite the various facts that many researchers have discovered various recognized models, many of them are unable to accurately perform better algorithms (Liu et al. 2019). Many applications can be developed to predict accurately for sensitivity from various platforms.

The novel convolutional neural network algorithm has the drawback of not being user-friendly and is very time-consuming. This means that the novel convolutional neural network algorithm is not easy to use and takes a lot of time processing the data (Tanner 1983). In the future, this bone age prediction using x-ray images can be further improved by developing the novel convolutional neural network (Rajvanshi and Dhaka 2016; Prateek et al. 2019).

CONCLUSION

From this study of bone age prediction using x-ray images, the mean accuracy of K-Nearest Neighbor algorithms is 70.26% whereas novel convolutional neural networks have a higher mean accuracy of 82.36%. Hence it is inferred that the novel convolutional neural network is better in accuracy when compared to K-Nearest Neighbor algorithms.

DECLARATIONS

Conflict of Interest

No conflict of interest in this manuscript.

Authors' Contribution

Author MA was involved in data collection, data analysis, and manuscript writing. Author RK was involved in conceptualization, data validation, and critical reviews of the manuscript.

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Tables and Figures

Table 1. Pseudocode for Convolutional neural networks

// I: Input dataset records
1. Import the required packages.
2. Convert the image into machine-readable after the extraction feature.
3. Assign the image to the output variables.

4. Using the model function, assign it to the variables.
5. Compiling the model using metrics as accuracy.
6. Evaluate the output
7. Get the accuracy of the model.
OUTPUT //Accuracy

TABLE 2. Pseudocode for K-Nearest Neighbors

// I: Input dataset image
INPUT: Capture Image
Step 1. Pre-process the image of the particular x-ray.
Step 2. Segment and normalize the images.
Step 3. Extract the feature vector of each normalized candidate
Step 4. Train K-Nearest Neighbors based on a saved sample database.
Step 5. Recognize the bone age by the set of K-Nearest Neighbors trained in advance.
Step 6. If there are no more unclassified samples, then STOP.
Step 7. Add these test samples into their corresponding database for further training. OUTPUT: Bone age prediction.
OUTPUT //Accuracy

Table 3. Group, Accuracy, and Loss value uses 8 columns with 8 width data for bone age prediction.

SI.NO	Name	Type	Width	Decimal	Columns	Measure	Role
1	Group	Numeric	8	2	8	Nominal	Input
2	Accuracy	Numeric	8	2	8	Scale	Input
3	Loss	Numeric	8	2	8	Scale	Input

Table 4. Group Statistical analysis for Novel convolutional neural network and K-nearest neighbors Algorithm Mean, Standard Deviation and standard error mean are determined.

	Group	N	Mean	Std Deviation	Std.Error Mean
Accuracy	CNN	10	82.2250	0.10146	0.03208
	KNN	10	70.1570	.06516	.02060
Loss	CNN	10	17.7380	.07983	.02525
	KNN	10	29.8430	.06516	.02060

Table 5. Independent sample T-test t is performed on two groups for significance and standard error determination. The p-value is greater than 0.05 (.389) and it is considered to be statistically insignificant with a 95% confidence interval.

		Levene's Test for Equality of variance		T-Test for equality of mean						
				t	df	Sig(2-tailed)	Mean difference	Std.Error Difference	95% confidence of Difference	
		F	Sig						Lower	Upper
Accuracy	**Equal variances assumed**	5.069	.037	316.485	18	.000	12.06800	.03813	11.98789	12.14811

	Equal Variances not assumed			316.485	15.344	.000	12.06800	.03813	11.98688	12.14912
Loss	**Equal variances assumed**	.779	.389	-371.471	18	.000	-12.10500	.03259	-12.17346	-12.03654
	Equal Variances not assumed			-371.471	17.305	.000	-12.10500	.03259	-12.17366	-12.03634

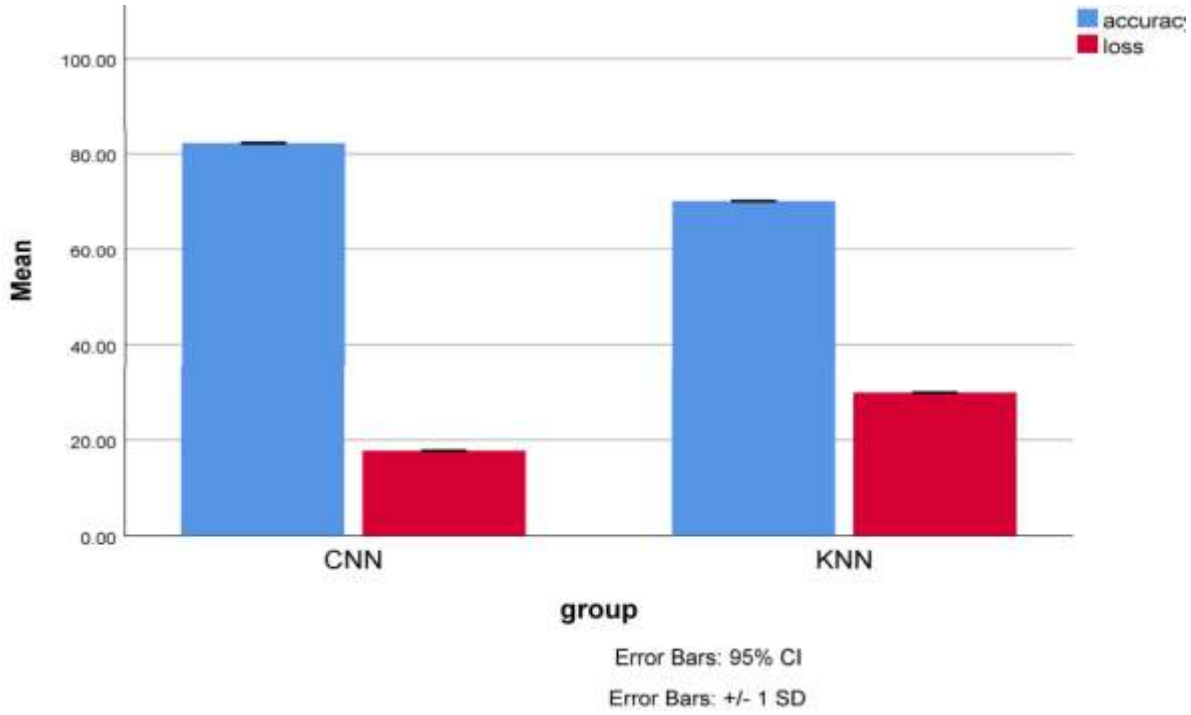

Fig. 2. Comparison of Novel Convolutional neural network and K-Nearest Neighbors Algorithm in terms of mean accuracy. The mean accuracy of the Novel Convolutional neural network is better; than the K-Nearest Neighbors Algorithm. The standard deviation of the Novel Convolutional neural network is slightly better than the K-Nearest Neighbors Algorithm (Gilsanz and Ratib 2011). X-Axis: Novel Convolutional neural network vs K-Nearest Neighbors. Y-Axis: Mean accuracy of detection ± 1 SD.