IMPROVING ACCURACY FOR BONE AGE PREDICTION FROM X-RAY IMAGE USING CONVOLUTIONAL NEURAL NETWORK TECHNIQUE OVER SUPPORT VECTOR MACHINE

Ashok M[1], Rashmita Khilar[2*]

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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 Support Vector Machine. **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 0.2. **Result:** Mean accuracy of convolutional neural network (82.36%) is high compared to support vector machines (74.84%). The significance value for accuracy and loss is 0.028 ($p<0.05$). **Conclusion:** The mean accuracy of the bone age prediction system in convolutional neural networks is better than the support vector machine.

Keywords: Novel Convolutional Neural Network, Support Vector Machine, Accuracy, Prediction, Bone Age, Chronological.

[1]Research Scholar, Department of Information Technology, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu, India, Pincode: 602105.
[2]Department of Information Technology, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamilnadu, India, Pincode: 602105.

1. Introduction

Bone age prediction can be useful in a variety of situations. For example, it may be accustomed to predict what proportion longer a baby can grow, after they can hit a time of life or maybe their final height. It can also be used to monitor the progress of children being treated for conditions that affect growth (Lei et al. 2019; Harmsen et al. 2013). Bone age prediction is also very useful when it comes to identifying people lacking proper identification. In recent years, there has been a significant increase in the number of refugees lacking proper identification seeking asylum in Europe (Wang et al. 2016; Dufau et al. 2019). Unaccompanied individuals under the age of 18 are eligible for special rights according to the United Nations Convention on Rights of the Child, so from a legal standpoint, an accurate assessment is important to create a fair procession age prediction using x-ray images is an important application (Stoyanov et al. 2018; Amasya et al. 2020). Some of the applications of bone age prediction are the study helps doctors estimate the maturity of a child's skeletal system. It's usually done by taking a single X-ray of the left wrist, hand, and fingers. It is a safe and painless procedure that uses a small amount of radiation. applications that include eye disease detection, Alzheimer diagnosis, COVID-19 screening, physiotherapy, and cardiac analysis. However, the input images will come in various sizes and conditions, where some images will be relatively small for the newborn baby and vice versa for the late teen case (Hochberg 2002; Gaskin et al. 2011; Tanner 2001). Nowadays bone age prediction is applied in cybercrime departments, diagnosis of orthopedic related problems.

In this research work, Bone Age prediction has been carried out by researchers, and 80 related research articles in IEEE Digital Xplore and 40 articles are published in research gate. Assessment of a child’s skeletal maturity is important for the management of skeletal disorder during growth (Amasya et al. 2020). Differences between skeletal age and chronological. Therefore BAA is an important tool in the monitoring of growth, and to diagnose and manage a multitude of endocrine disorders and pediatric syndromes (Zulkifley, Abdani, and Zulkifley 2020). Bone age has also been used for computing the ultimate adult height of youngsters in traditional healthy kids and might be employed in determinant age where birth records don’t seem to be accessible (Mellits, Dorst, and Cheek 1971). The collected data is compared against the taken dataset of Convolutional Neural Network (Yoo et al. 2013). Bone age classification using convolutional neural networks (CNN) as a support tool for related disciplines in bone age diagnosis. Although different types of study for bone age evaluation using CNN have been conducted, the attention mechanism has not been thoroughly compared to standardized atlas collection of hand radiography for bone age assessment (Tanner 1983). The regressor network, that is employed to predict the age has utilized three-layer residual dissociable convolution units to provide a deep network, however, maintain a suitable model size, which is around 20,000,000 parameters. The network has also been trained using variable learning rates where its value is linearly decreasing concerning the training epoch (Jhang and Cho 2019) (Jhang, Kang, and Kwon 2020).

Our institution is keen on working on latest research trends and has extensive knowledge and research experience which resulted in quality publications (Rinesh et al. 2022; Sundararaman et al. 2022; Mohanavel et al. 2022; Ram et al. 2022; Dinesh Kumar et al. 2022; Vijayalakshmi et al. 2022; Sudhan et al. 2022; Kumar et al. 2022; Sathish et al. 2022; Mahesh et al. 2022; Yaashikaa et al. 2022). The current system of predicting bone age has certain limitations in detecting the difference between a child's bone age and chronological age, which could signal a growth problem. However, such differences do not always imply that there is a disadvantage, as even perfectly healthy children will have bone ages that differ from their recorded ages. Even though much study has been done on this subject, there is still a gap in terms of formulating performance when it comes to automatically detecting and recognizing bone age. As a result, an automatic system to forecast and recognize number plates is necessary. The goal of this research is to use innovative convolutional neural networks to automatically predict and recognize bone age, hence boosting performance and lowering the rate of erroneous predictions.

2. 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 predicting the bone age from an x-ray image, to modify the problem of low accuracy rate, convolutional neural networks and support vector machines are used. Convolutional neural networks learn about the age of the bone approximately. The support vector machine enables thorough exploration of bone age data present. The mean accuracy of convolutional neural networks is 82.36%. The mean accuracy of the support vector machine is 74.84%. Dataset for this instance is collected from (https://www.kaggle.com/saksham219/bone-ag-prediction- through-x-rays/data ?select=boneage-training-dataset) website with 12,611 instances (Kim et al. 2015).

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're used in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, and natural language processing, among other things.

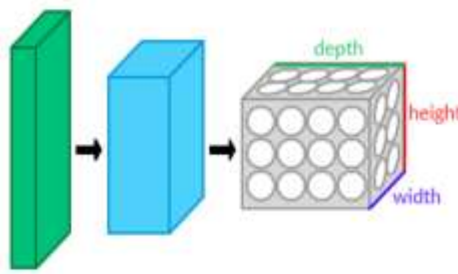

Fig. 1. Convolutional neural network

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 feedforward 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.

Support-vector machines (SVM), also known as support-vector networks, are supervised learning models that examine data for classification and regression analysis. SVMs, which are based on statistical learning frameworks and Chervonenkis, is one of the most reliable prediction systems (1974). An SVM training algorithm creates a model that assigns new examples to one of two categories, making it a non-probabilistic binary linear classifier, given a series of training examples, each marked as belonging to one of two categories (although methods such as Platt scaling exists to use SVM in a probabilistic classification setting).

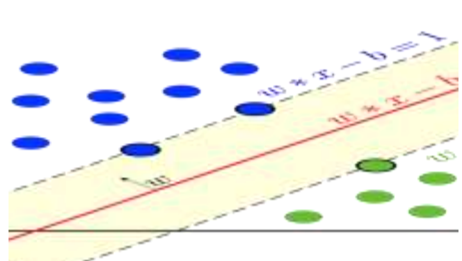

Fig. 2. Support vector machine

In machine learning, classifying data is a typical problem as explained in Fig. 2. Assume that some data points are assigned to one of two classes, and the purpose is to determine which class a new data point will be assigned to. A data point is viewed as a display style pp-dimensional vector (a list of display style pp numbers) in support-vector machines, and we want to know if we can separate such points with a display style (p-1)(p-1)-dimensional hyperplane. Pseudocode for the support vector machine is 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 support vector machine. Group is given as 1 for convolutional neural network and 2 for support vector machine, 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 independent variables in Bone age detection were Height, Depth, Width, Carbon content, calcium value and dependent variables were Accuracy and Precision. The significance values of proposed and existing algorithms contain group statistical values of the algorithms.

3. Results

In statistical tools, the total sample size used is 20. This data is used for the analysis of convolutional neural networks and support vector machines. Statistical data analysis is done for both the prescribed algorithms namely convolutional neural networks and support vector machines. 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 support vector machine are denoted. The Group statistics table shows several 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. Fig. 3, shows a comparison of the mean accuracy and mean loss between the convolutional neural network and support vector machine.

4. Discussion

From the results of this study, Convolutional neural networks are proved to be having better accuracy than the support vector machine. Convolutional Neural Network has an accuracy of 82.36% whereas support vector machine has an accuracy of 74.84%. The group statistical analysis on the two groups shows that Convolutional neural networks (group 1) have more mean accuracy than support vector machines (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 fact 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(Harmsen et al. 2013). This means that the novel convolutional neural network algorithm is not easy to use and takes a lot of time processing the data. In the future, this bone age prediction using x-ray images can be further improved by developing a novel convolutional neural network.

5. Conclusion

From this study of bone age prediction using x-ray images, the mean accuracy of support vector machine algorithms is 74.84% 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 support vector machine 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 Novel 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 Support Vector Machines

// 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 SVMs based on a saved sample database.
Step 5: Recognize the bone age by the set of SVMs 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:** Prediction bone age.
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 Support vector machine Algorithm Mean, Standard Deviation, and standard error mean is determined.

	Group	N	Mean	Std Deviation	Std.Error Mean
Accuracy	CNN	10	82.2250	0.10146	0.03208
	SVM	10	74.6500	.14974	.04735
Loss	CNN	10	17.7380	.07983	.02525
	SVM	10	25.3500	.14974	04735

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 (0.028) 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	2.181	.157	132.434	18	.000	7.57500	.05720	7.45483	7.69517
	Equal Variances not assumed			132.434	15.825	.000	7.57500	.05720	7.45364	7.69636
Loss	Equal variances assumed	5.700	.028	-141.852	18	.000	-7.61200	.05366	-7.72474	-7.49926
	Equal Variances not assumed			-141.852	13.734	.000	-7.61200	.05366	-7.72730	-7.49670

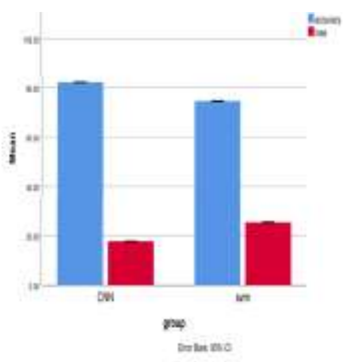

Fig. 3 Comparison of Novel Convolutional neural network and Support vector machine Algorithm in terms of mean accuracy. The mean accuracy of the Novel Convolutional neural network is better than the Support vector machine Algorithm. The standard deviation of the Novel Convolutional neural network is better than the Support vector machine Algorithm. X-Axis: Novel Convolutional neural network vs Support vector machine. Y-Axis: Mean accuracy of detection ± 1 SD.