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Graph Convolutional networks for drug response prediction

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ABSTRACT

Improving techniques for assessing hypertension and blood pressure from clinical and physiological data is the main focus of this work. Methods and Supplies: Two groups use the PPG-BP dataset for non-invasive blood pressure prediction: K-Nearest Neighbors (N=10) and Novel Convolutional Neural Network (N=10). There are 500 patients' blood pressure readings in the dataset; 250 are male and 250 are female. The measurements are 905,400 by 875 labels. The findings reveal that when it comes to accuracy, Novel Convolutional Neural Network (73.3980%) beats K-Nearest Neighbors (61.5060%), with a significance value of 0.001 (independent sample t test $p<0.05$). This demonstrates, statistically speaking, that the two approaches are statistically separate. So, Novel Convolutional Neural Network is better than K-Nearest Neighbors in determining blood pressure from physiological data.

Anxiety, affordable medicine, hypertension, K-nearest neighbor, neural networks, and innovative convolutional neural networks are all keywords related to this article.

INTRODUCTION

The prevalence of hypertension as a worldwide health concern has been steadily increasing in recent years. Medical experts recommend checking blood pressure every day, but few patients really follow this recommendation. This research proposes a method for detecting a person's pulse before taking their blood pressure—a non-contact approach. The experiment included sending and receiving 2.4GHz microwave signals from a participant in order to quantify the reflection intensity as it changed over time [1]. In order to avoid the need for a cuff, this study suggests employing transfer learning in conjunction with short-duration photoplethysmograms (PPGs) to monitor blood pressure (BP). The suggested technique utilizes deep Convolutional Neural Networks to estimate BP while using a modest computing budget [2]. Providing a gradient boosting regression model–based technique for blood pressure estimation is the goal of this

study. A photoplethysmography was evenly separated from the MIMIC II database to produce an accurate measurement of blood pressure. Using these qualities, one may approximate the patient's blood pressure readings [3]. This study's practical application introduces a hypertension risk prediction system that uses an integrated multi-agent architecture to fill in missing values in time series and provide individual risk assessments. Using input data that has been improved using Gaussian mixture models, an OIESGP can forecast blood pressure in real time [4][4][4]. The project's primary target is hospital-based blood pressure detection systems. This research includes the following parameters: anxiety, hypertension, cheap drug, blood pressure, health, K-nearest neighbor, neural network.

Improved methods of measuring hypertension and blood pressure have been the subject of much study in recent years. Among the over 420 publications archived by IEEE Xplore, one proposes using Convolutional Neural Networks (CNN) to automatically generate features from pulse wave data and estimate blood pressure. Using cuffless blood pressure estimates from PPG alone as the gold standard, we evaluate CNN's performance in this research [3, 5]. In order to construct a DNN-DBN regression model and comprehend the intricate nonlinear relationship between the reference nurse's blood pressure readings and the fabricated feature vectors created by oscillometric waves. Pretraining allows our DBN-DNN, a robust generative network for feature extraction, to remain in local minima [6]. Machine learning methods are used to estimate cuff-less blood pressure, and PAT values are extracted by denoising signals with advanced filtering. Verification of the findings is done using AAMI and BHS methods. The AAMI requirements are satisfied by the DBP and MAP estimate method. According to [7], CatBoost achieved Grade A accuracy with MAP and DBP data. The correlations between photoplethysmography, electrocardiogram, and mobile blood pressure are investigated in this research using random forest. This was accomplished by extracting 18 features from the PPG and ECG. The models employed beat-to-beat ABP as an output and the most relevant characteristics as inputs [8]. This work employed conditional mutual information maximization (CMIM) to identify the most effective SNPs to combine with several classification methods for hypertension illness detection [9].

The current system's lack of precision has shown a research need. The main objective of this research is to compare the Novel Convolutional Neural Network methodology to the K-Nearest Neighbors method for increasing classification accuracy. Compared to the K-Nearest Neighbor technique, the Novel Convolutional Neural Network algorithm's accuracy is improved by the suggested model.

MATERIALS AND METHODS

Researchers from the Saveetha School of Engineering's Computer Science and Engineering Department conducted the investigation at their data analytics lab. A G-power test with a power of 0.85 and $\alpha = 0.05$ was used to compute the sample size in ClinCalc software by comparing the two controllers. In order to compare the procedure, we divide the participants into two groups and calculate their results. There are a total of 10 samples chosen for this study, with 10 sets of samples chosen for each group. Technical analysis software is used to develop two algorithms: the algorithm for Novel Convolutional Neural Networks and the K-Nearest Neighbors technique. Ten people have been selected at random for each group.

The dataset used in this work, which includes all the variables for blood pressure and hypertension prediction, may be seen on the "Kaggle" website, namely at https://www.kaggle.com/datasets/lntphuong/notebook-with-ppgbp-data [3]. Clinicians gather this information utilizing photoplethysmography (PPG) technology, an inexpensive and easy optical measuring method often used for heart rate monitoring. Light and a photo detector applied to the skin surface allow the non-invasive PPG gadget to assess the volumetric variations in blood circulation. The patient's sex, age, height, blood pressure (systolic and diastolic), heart rate, body mass index (BMI), and other relevant clinical data are collected via testing. This research includes the following parameters: anxiety, hypertension, cheap drug, cerebral cortex, K-nearest neighbor, well-being, and BP.

Python & the OpenCV package are used to build and perform the suggested work. We used Windows 10 as our platform to test deep learning. The hardware setup included a 4GB RAM stick and an Intel Core i7 CPU. The 64-bit system sort was used. We utilized the Java programming language to put the code into action. When it comes to running the code, the dataset is used to execute an output process with precision.

Revolutionary Convolutional Neural Technology

An example of a Deep Learning technique, a Convolutional Neural Network (CNN) may take an input picture, assign learnable weights and biases to different parts of the picture, and then differentiate between them. A ConvNet, in comparison to other classification systems, needs much less pre-processing. In contrast to basic approaches, ConvNets may learn these filters and attributes automatically.

Similar to how the human brain's neural networks are structured, the Visual Cortex served as inspiration for the Convent's architecture. Neurones can only react to stimuli within a small area known as the Receptive Field in the visual field. The whole visual field is filled when these fields overlap. The right filters may allow a convent to record the picture's spatial and temporal correlations. A better fit to the image dataset is produced by the design, thanks to the reuse of weights and the reduction of parameters to be considered. Put simply, the network may be taught to understand the image's complexity level better.

By inputting images labeled with words like "dog," "cat," "lion," "tiger," etc., CNN is able to classify and manage the images. A picture's resolution determines how the computer will see it as a pixel array. The image resolution determines how the dimensions are interpreted, but generally speaking, they are h*w*d. A 4*4*1 matrix array, for instance, stands in for a grayscale image, while a 6*6*3 matrix array denotes an RGB picture. Multiple convolutional, pooling, fully connected, and filter layers (often called kernels) process each input picture in a convolutional neural network (CNN). Next, we'll employ probabilistic values between 0 and 1 to classify an item using the Soft-max algorithm.

Algorithm:

Setting the model's parameters, such as the layer-specific biases and weights, is the first stage.

Secondly, iterate over the training data until you reach the end.

Thirdly, load a set of images into the convolutional layer.

Fourth, use the filters to conduct a convolution operation; then, apply the activation function, bias, and adjustments.

The fifth step is to use max pooling to make the feature maps smaller in size.

Step 6: Proceed to the fully connected layers by repeating the previous stages for each successive layer, including the convolutional and pooling layers.

The seventh stage is to smooth the input including output of the last pooling layer, all of the fully linked levels, and the connected layers themselves.

Eighth Step: Apply the activation function, add bias, and multiply the inputs and weights matrices.

Step 9: Find the difference (error) between the actual labels and the expected outputs.

Step 9 involves computing the cost's partial derivatives with respect to the parameters. Step 10 involves updating each layer's weights and biases using gradient descent.

Eleventh Step: Use the trained network to make predictions on fresh data.

Step 12: Finalize.

K-Nearest Apparent

Under the premise that the new instance is similar to the current instances, the K-NN method assigns it to the category that best matches the current instances. Following the storage of all previous data, the K-NN method is used to categorize incoming data points according to their similarity. The K-NN approach may be used to correctly and quickly sort new data into the appropriate category. While the K-NN method is often used for classification tasks, It may also be used to problems with regression. Because it doesn't immediately start learning from the training dataset but instead stores it, this approach is frequently called a lazy learner. Instead, it uses the dataset to take action when classifying data. The KNN method only saves the data during training; in response to fresh input, it assigns it to a category that most closely fits the new data.

The K-Nearest Neighbor Algorithm

First things first: bring in all the required packages.

The second step is to transform the datasets into numerical values after package extraction.

Third, find the formula for the distance between two points, "d(x, xi)" where i ranges from 1 to n and d is the standard distance between points in the Cartesian coordinate system.

Stage 4: Sort the computed n-dimensional geometric distances in a non-decreasing sequence.

Fifth Step: Using this sorted list, pick the top k distances, where k is an integer from 0 to 1.

Locating the k-points that correspond to these k-distances is the sixth step.

In Step 7, if there are k points & k is not equal to zero, then substitute ki for the ith class's number of points.

Step 8: Assign x to class i if ki is greater than kj for all $i \neq j$.

The ninth step is to build the confusion matrix.

Seeing the outcome from the training set graphically is the tenth step.

Visualizing the test set outcome is the eleventh step.

Statistical Analysis

We test the K-Nearest Neighbors and Novel Convolutional Neural Network approaches statistically using SPSS version 26. Images, physical objects, physical distance, frequency, modulation, amplitude, volume, and decibels are all examples of things that may be thought of as independent variables. Examples of dependent variables include pictures and real-life items. Both procedures are checked for correctness using an independent T test.

RESULTS

In Table 1, we can see the Novel Convolutional Neural Network algorithm's projected loss and accuracy. The anticipated accuracy and loss of the K-Nearest Neighbors method are shown in Table 2. The statistical statistics that may be utilized for comparison are calculated using these 10 data samples and the loss values of each procedure. The findings show that the Novel Convolutional Neural Network approach achieved an average accuracy of 73.3980%, whereas the K-Nearest Neighbors strategy achieved an average accuracy of

61.5060%. In Table 3, we can see the average accuracy values for both the Novel Convolutional Neural Network approach and the K-Nearest Neighbors methodology. With a standard deviation of 3.22397 vs. 1.97162, the Novel Convolutional Neural Network technique achieves better mean value performance than the K-Nearest Neighbors algorithm. Table 4 shows the outcomes of the Independent sample T test for the K-Nearest Neighbors technique and the Novel Convolutional Neural Network approach, with a significance value of 0.001 ($p<0.05$). This demonstrates, statistically speaking, that the two approaches are statistically separate. Table 5 compares the K-Nearest Neighbors method's accuracy with that of the Novel Convolutional Neural Network methodology. Both the K-Nearest Neighbors and Novel Convolutional Neural Network methods' average accuracy and loss are shown in Table 1. You can see the two methods side by side in Figure 1.

The parameters for the Novel Convolutional Neural Network method are 73.3980 for the mean, 3.22397 for the standard deviation, and 1.01951, for the standard error mean. The K-Nearest Neighbors method also has a mean of 61.5060, a standard deviation of 1.97162, and a standard error mean of.62348. Contrarily, the Novel Convolutional Neural Network technique has loss values of 26.6020 for the mean, 3.22397 for the standard deviation, and 1.01951 for the standard error mean. This research includes the following parameters: anxiety, hypertension, cheap drug, blood pressure, health, K-nearest neighbor, neural network.

In addition to the two methods' standard deviations, means, and standard error measures, the group statistics value is also given. There are two ways, Here we compare the Novel CNN method with the K-Nearest Neighbors technique graphically, showing their respective loss means. In comparison to the K-Nearest Neighbors algorithm's 61.5060% categorized accuracy, the Novel Convolutional Neural Network algorithm's 73.3980% accuracy is much greater.

DISCUSSION

According to the study's results, the Novel Convolutional Neural Network method outperforms the K-Nearest Neighbors approach, with a significance level of 0.001 ($p<0.05$). With an accuracy of 73.3980% compared to 61.5060%, the Novel Convolutional Neural Network approach significantly surpasses the other technology.

The primary objective of this research is to find a non-invasive way to take a person's blood pressure and detect their pulse. Humans participated in the experiment by transmitting and receiving microwave radiation at a frequency of 2.4GHz [2]. An astounding 85-89% accuracy is achieved by the suggested procedure, as stated in the source. By introducing short-term changes to the pulse waveform, this research suggests a method that can avoid calibration. The suggested approach has the potential to reliably determine diastolic blood pressure (DBP) to the tune of 89.4 percent [10]. Our artificial neural network (ANN) models may potentially outperform earlier efforts without the need for demographic or technical data. When utilizing this strategy, an accuracy of around 86.47% has been recorded [11], [12]. Using information from photoplethysmography (PPG) and electrocardiography (ECG), this study presented a cuffless BP calculation technique [13] that is sufficiently accurate. This research considers an array of elements, including hypertension, anxiety, K-Nearest Neighbor, innovative convolutional neural networks, blood pressure, inexpensive treatment, and neural networks [4].

The time required to train a Novel Convolutional Neural Network technique is a significant drawback of our research, particularly when working with huge datasets. We need to include additional features into the system to expedite the training of the data set, according to the future intentions of this study.

CONCLUSION

Using clinical and physiological data in combination with the K-Nearest Neighbors approach and the Novel Convolutional Neural Network algorithm, this research aims to find more exact methods to detect blood pressure and hypertension. With an accuracy of 73.3980%, the Novel Convolutional Neural Network technique outperforms the K-Nearest Neighbors strategy, which achieved 61.5060%. According to the findings, K-Nearest Neighbors is beaten by Novel Convolutional Neural Networks.

DECLARATIONS

Potential Litigation:

There is no potential bias in this paper.

The Role of the Authors

Data collection, data analysis, and paper preparation were the responsibilities of Author RD. Author KM contributed to the brainstorming, data validation, and text reviews.

Praise and Honor

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TABLES AND FIGURES

Table 1: Loss and Accuracy Analysis of the New Convolutional Neural Network Method

Iterations	Accuracy(%)
1	69.54
2	69.67
3	70.98
4	71.15
5	72.95
6	73.36
7	75.36

8	74.35
9	77.74
10	78.88

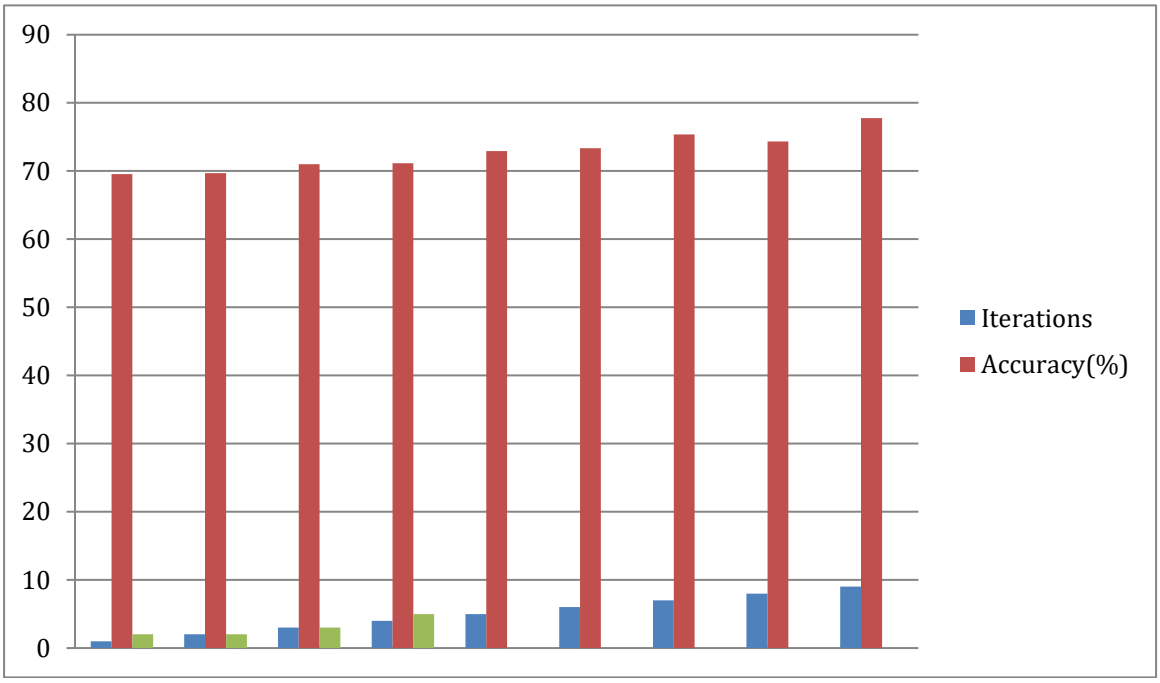

fig.1 New Convolutional Neural Network Method

Table 2: K-Nearest Neighbors Algorithm Accuracy and Loss Analysis

Iterations	Accuracy(%)
1	59.36
2	58.63
3	59.89
4	61.01
5	62.01
6	64.97
7	62.12
8	63.96
9	61.01
10	62.1

Table 3. Comparison of the K-Nearest Neighbors technique versus a new convolutional neural network approach using group statistics. Three metrics are computed for a total of 10 samples: mean, standard deviation, & standard error mean.

	Group	N	Mean	Average Distinction	Typical Error Mean
Accuracy	Revolutionary Convolutional Neural Network Method	10	73.3980	3.22397	1.01951
	K-Nearest Neighbors algorithm	10	61.5060	1.97162	.62348

Table 4. With a p-value of 0.001 ($p<0.05$), the Independent Sample T-test reveals that the Novel CNN method outperforms the K-Nearest Neighbors approach.

		Levine's test for variance equality		The equality of variance test by Levine						
		f	**Sig.**	**t**	**df**	**Notable (2-tailed)**	**Average variation**	**Variation in standard error**	**Lower**	**Upper**
Accuracy	Assumed to be equal variances	2.328	0.001	9.951	18	0.001	11.89200	1.19504	9.38131	14.40269
	No assumption of equal variances made			9.951	14.906	0.001	11.89200	1.19504	9.34343	14.44057

Table 5. Analyzing the performance of A Novel Convolutional Neural Networks Algorithm with K-Nearest Neighbors

CLASSIFIER	ACCURACY(%)
Revolutionary Convolutional Neural Network Method	73.3980
K-Nearest Neighbors algorithm	61.5060

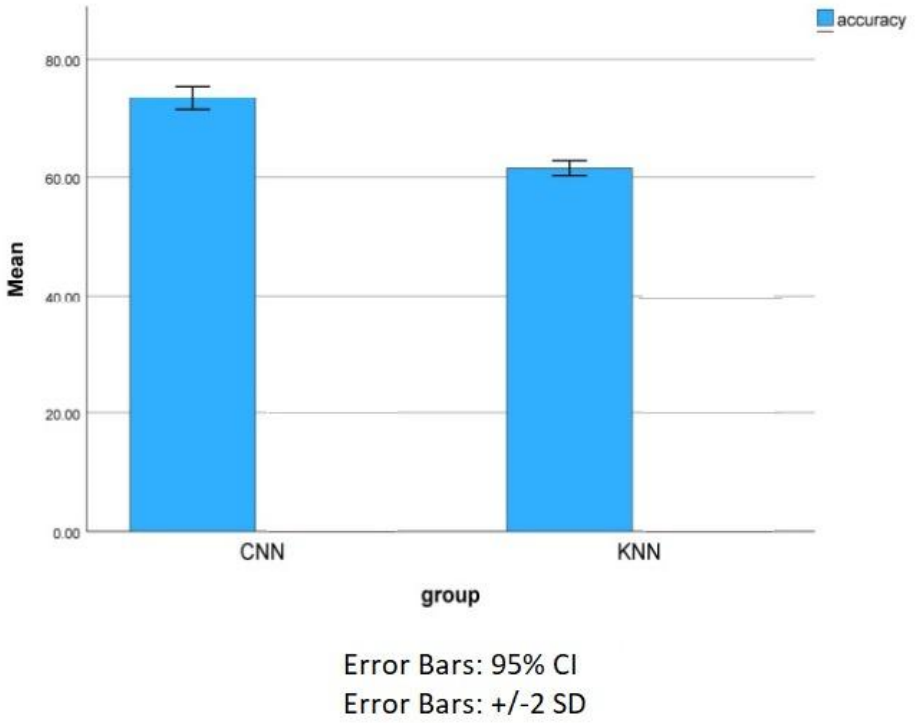

Fig. 1. Here, we evaluate K-Nearest Neighbors against a new convolutional neural network approach. Classifier in terms of mean accuracy and loss. In comparison to K-Nearest Neighbors, the Novel Convolutional Neural Network approach achieves better mean accuracy. System for categorizing data: Compared to K-Nearest Neighbors, the Novel Convolutional Neural Network approach has a somewhat less standard deviation. This classifier's Y-axis displays the average detection accuracy, with a plus or minus two standard deviations margin of error.