



An Investigative Analysis on Mapping X-Ray to Live Using Convolution Neural Networks for Detection of Genu Valgum

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Abstract

Introduction: Bow Legs and Knock Knees are quite common in growing children, which usually affect the lower portions of the body, however such disorders usually do not have any pathological significance. In this paper, we investigate a method using deep learning to correctly draw a boundary between a physiologically normal knee and a genu valgum. *Objective:* To draw a decision boundary between what is classified as Normal and what is “Abnormal” *i.e.* a knee exhibiting features of Knock knees which is Genu Valgum by using AI and ML tools. *Methods:* For this study the Adam Gradient descent was used which is a combination of *AdaGrad* and *RMSPProp*. There is also an implementation of grid search for “self-selection” of parameters by the neural network which is the unique point that most existing ML algorithms on account of self-learning capability much like un-supervised learning but limited to parameter selection. In the second part, we try to investigate the outcome using X-ray version of the disorder and try to compare if the result is truthful in accordance to the patient’s case. *Results:* The two types of Knees had been correctly classified up to an accuracy of 89% to 90% (by using normal to normal) which is really good for most physicians or sports instructors to use as an initial screening tool for most athletes/patients. However, the second part shows interesting results with an accuracy of 60% (X-ray to Normal).

Subject Areas

Artificial Intelligence, Bioengineering

Keywords

Recommendation Systems, Artificial Neural Networks, Convolutional Neural Networks, Biomechanics, Knock Knees, Genu Valgum, Informatics

1. Introduction

Bow Legs (Genu Varum) and Knock Knees (Genu Valgum) are usual in growing children that affects the lower portions [1]. Most of these problems represent normal physiological development and are usually self-correct with changing time [1]. These cases usually do not require treatment. However, it is important for the physician to correctly differentiate between physiological deformities and those which would be pathological [2]. Without proper differentiation between the two, a treatment cannot be planned. Most inexperienced physicians would have trouble identifying the two if they both look identical.

Symptomatic Bow legs and knock knees are common in aging athletes. Diagnosis in such cases is made by observation and use of standing alignment X-rays which typically give away narrowing of joint surfaces on one of the sides. Treatment usually is focused on non-steroidal anti-inflammatory drugs and heel wedge. Heel Wedges have been the basis of conservative treatment in the case of most knee deformities [2].

The simplest mode of diagnosis is by standard X-ray imaging where a knee with genu-valgum would show a normal physis, epiphysis, metaphysis but an abnormal tilted horizontal axis [3].

Typically, there are two kinds of Knock Knees physiological and pathological but pathological is typically much less common. It has been observed that children with pathological genu valgum bear tibiofemoral angles outside the two standard deviations but this changes with age [4].

Genu Valgums can appear worse clinically than with radiographic images; this is because pain is often the most relevant patient complaint [5].

In Sports Knock Knees is a cause for concern for most athletes. As the athletes grow physically they begin to exert more force on the knees [6]. But the force developed can be more in one compartment than the other. In the case of Valgus Knees this force occurs at the “lateral compartment” which can cause stretching of the medial ligaments [6]. For females usually, they have wider hips which causes a larger increase of the angle at which the femur directs towards the centreline of the body [6]. Athletes have learnt to manage the behaviour of such problems by using ankle bands/cuffs just above the knee during a squat session [6].

Neural networks play a very important role in most decision-making systems earlier studies by use of neural networks transcends barriers in finance to healthcare to automatic driving cars. The next few works shows some successful outcomes of using neural networks in most applications.

Neural networks had been used for predicting movement of stock markets [7]. Neural networks have also been and are currently used in many domains of diagnostic medicine including cancer detection [8]. Pedestrian detection systems have also been tested and tried by making use of CNN (Convolutional Neural Networks) as in the case of [9]. Skin Cancer based detection systems have also been developed by making use of CNN to perform dermatologist level decision

making [10]. A study which was done to evaluate the best approach of classification in the case of medical images showed that the use of Multi-Layer Perceptron typically yielded higher accuracy than naïve Bayes classifiers [11].

So, it is observed that CNN's have been a very successful model for most detection systems relating to medical image diagnosis. Our design would rely on a slightly modified CNN architecture.

Aim of This Study

This designed system can help a physician draw a correct boundary between what type of knees should require surgery and which type of knee should not require surgery but should still be classified as knock knees for medical assessment purposes. However, a different approach has been taken for this we are trying to relate how the model can predict if a patient has Genu Valgum from the X-ray-mapping as a test set.

This system can also be extended to the use as a screening tool by sports instructors to identify the severity of knock knees in them which could impair running and cause knee pain if left un-treated for extended period of time

2. Methods

The focus here is in investigating which images that are fed into the system are correctly classified under the label of knock knees in order to evaluate the performance of our network. As stated in [12] that MLP yielded higher accuracy for categorization of medical images we use the same algorithm but in a different classification task. The dataset is a curated list of images of patients suffering from Genu Valgum which have been generated from various sources of which few of them have been obtained from Physiobank which a very good repository for valid medical data. However, the major goal is the correct decision-making process on the unknown image which would be feed from a live volunteered subject.

Our Classification problem would be binary in nature for the scope of this paper, as in two cases “Normal” knee and “Knock Knees” also called Genu Valgum. This second class “Normal” could also be a classification between Bow Knees or any other types of physiological shape disorder being considered in which case it would yield a multi-class problem.

A tuned CNN has been used. The algorithm here is the “adam” algorithm which is basically a technique of performing stochastic gradient descent on the CNN network. The process is explained in the next section.

Use of Adam: Adam is a very versatile algorithm for gradient descent when it comes to updating of weights. Research has shown that Adam is used as a benchmark for most neural networks. Paper [13] explains that Adam is pretty straightforward to implement and is computationally efficient and have low memory requirements. It also is immune to diagonal rescaling of gradients and is well suited for large amounts of data [13]. Adam combines the use of AdaGrad and RMSProp. AdaGrad is adaptive gradient *i.e.* as the gradient becomes low the

learning rate is “adaptively” reduced and vice versa which results in achieving faster convergence and in the case of RMSProp the moving average of gradients are taken. Adam considers both these features

Before the CNN can be initialized there are a few considerations mainly relating to the number of images in the training and test set, what would be the learning parameter, what should be the batch size and what would be the ideal epoch for this case.

Now the modification which has been done to the CNN is that instead of supplying user-defined parameters to the CNN, A choice of parameters have been given to the CNN and the CNN is supposed to make the “judgement” call on what parameters to pick and what would give the best accuracy and performance. The GridSearch technique has been used from keras library in this case for the selection of the best hyperparameters in this model.

There is still a problem with the existing dataset firstly the images which have been chosen in the dataset are not of the same size and also the size of the database is very limited (20 to 40 images) in either of the training and test sets. There would be a problem of overfitting if the dataset is too small meaning the neural network can “remember” the training set very well but yields poor performance and accuracy on the test set [13]. In order to deal with this a method called image augmentation has been performed which basically applies functions like “translation”, “rotation”, “shearing”, “zooming in”, “Zooming out”, etc. in order to create a greater number of sample images. This is very beneficial since the number of images can be augmented from the parent dataset by applying these transformations. This has been performed in the image pre-processing step.

One important point here is that the image has initially been manually separated into two folders characterizing the “knock” and “Normal” Knees.

Figure 1 gives the entire process of the modified network.

More literature on the working of CNN networks can be referred form this article here [14]. The steps involved in the network have been described in the representation above.

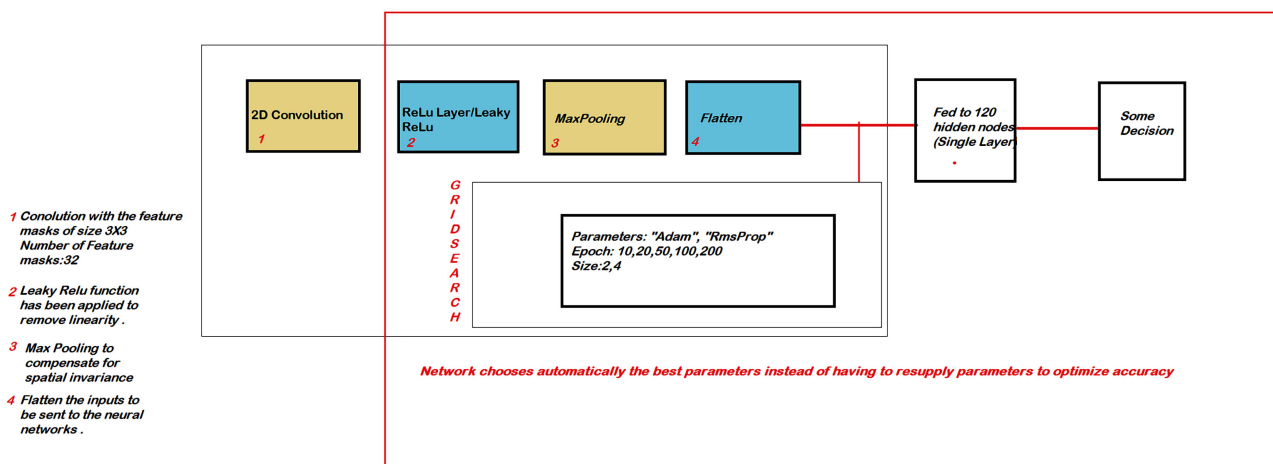


Figure 1. Modified CNN architecture.

3. Results and Evaluation

3.1. Testing on Normal to Normal Mapping

Figure 2 shows the sample test image set which have been used. The parameters are chosen based on the visibility of the exposed portions of the knee. Some parts of the images have been cropped so as to yield more information. The system yielded the best accuracy of 89% for this dataset which can be improved by supplying a greater number of epochs or changing the batch size. However, this is completely at the discretion of the operator considering the application to focus in.

The images were inputted as size of 64×64 and the output image size was also 64×64 . The best parameters were chosen by making use of grid search method (as explained in the diagram in **Figure 1**) However this accuracy can be further improved by making use of more epochs and supplying more varied batch sizes.

Figure 3 shows the unknown image which was used on the network to check the successful prediction.

However, the subject was also made to closely simulate a Genu Valgum to which the resulting predication was very successful (**Figure 4**).

Note. This study does not involve any kind of risk not greater than the daily dangers a person might face, a signed consent deemed to be not necessary by the Ethics Board.

Figure 5 shows a simulated Genu Valgum which was done to test the validity and performance of the model. **Figure 6** shows the results for this image.

3.2. Testing on X-Ray to Normal Mapping

For the training set we now introduce X-ray images to compare the performance of the network and to evaluate if neural networks have the ability to co-relate between the two or not.

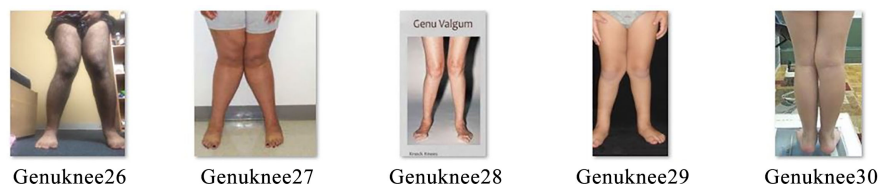


Figure 2. Sample Test set (All copyrights of individual images acknowledged).



Figure 3. Unknown image of control sample.

```
In [36]: training_set.class_indices
Out[36]: {'Genuvalgum': 0, 'Normal Knees': 1}
```

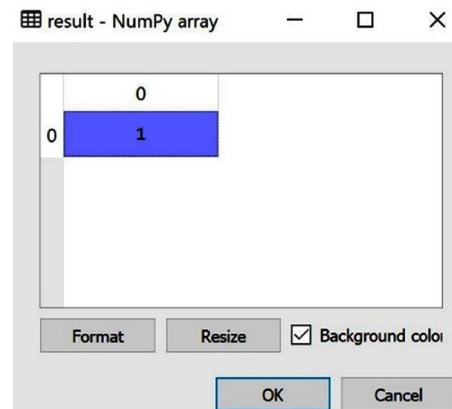


Figure 4. Subject yielded normal result.

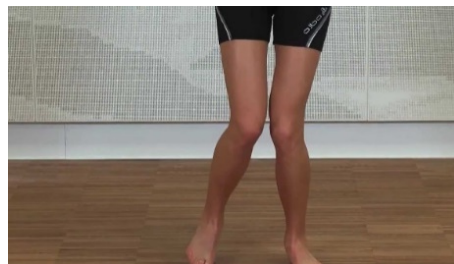


Figure 5. Simulated Genu Valgum (from the dataset).

```
In [78]: training_set.class_indices
Out[78]: {'Genuvalgum': 0, 'Normal Knees': 1}

In [79]: if results[0][0]==1:
...:     print('Normal')
...: else:
...:     print('GenuValgum')
GenuValgum
```

Figure 6. Successful outcome.

Figure 7 shows the sample X-ray images which have been used in this case.

Image in **Figure 8** have been used as the unknown (This image has been obtained from the patient) which the neural network does not know of. Typically, here the image is of the exterior organ formation whereas the dataset which have been modified are “X-Ray” Images.

Figure 9 shows the number of correct outcomes for every unknown image of the patient.

So there has been a 60 percent accuracy achieved in this model which can suggest that CNN can actually map some of the features from the x-ray images to the normal human knee to make meaningful prediction. However further studies on different cases other than the one mentioned need to be conducted to

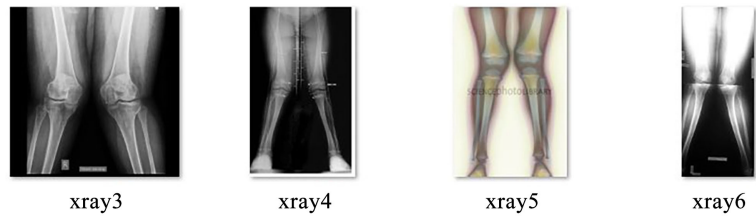


Figure 7. Sample portion of image used to train.



Figure 8. Image of patient with Knock Knees.

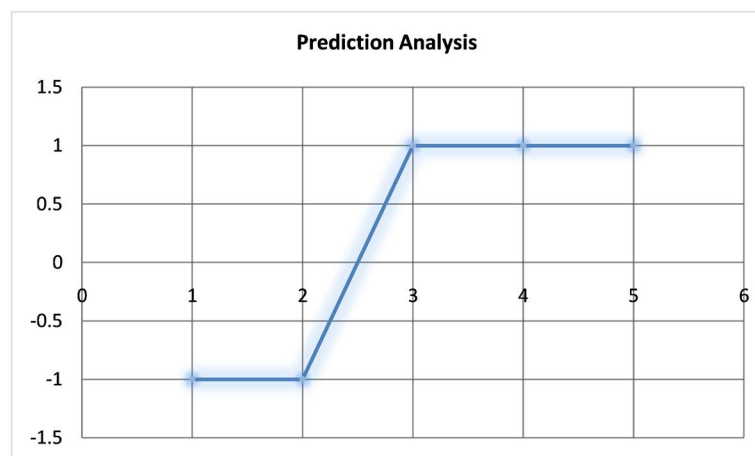


Figure 9. Three correct outcomes out of 5% - 60% accuracy.

ascertain the hypothesis. However, this accuracy can be further improved by making use of more images of X-ray of knees as training sets.

4. Discussion

Thus, the performance of the CNN has been evaluated in the automated detection of “knock Knees” in patient. The results were successful for the unknown image and yielded an accuracy of 90%+. However, it did not yield good accuracy (75%) on the test set which was presented. Reasons could be due to overfitting problem which can be eliminated by choosing the parameters wisely and more analytically or by making use of grid search which have been used in this application.

We also evaluated how CNN’s can react to different classes of images in the

training set, where we used X-ray images which are completely different class than normal images of the disorder and we have seen that it yielded 3/5 correct outcomes.

This can further be modified to yield Multi-Class Classification as decided by the physician/sport's instructor. Therefore, we conclude the successful outcome of CNN in classification of physiological shape disorders.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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