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A Machine Learning based Approach for Detection of Osteoarthritis using Thermal Images

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Abstract

Osteoarthritis (OA) of the knee is a common disorder that contributes to physical decline and activity limitation. Early OA diagnosis and treatment can stop the disease's progression. The assessment of a physician's visual examination is impartial, subject to different interpretations, and highly dependent on their level of experience. Therefore, a system that employs machine learning techniques to automatically determine the degree of knee OA has been proposed in this study. At first, a specifically created one stage YOLOv2 network is employed to estimate the size of the kneecap according to the distribution of knee joints in low contrast thermal images. To be more specific, the knee Kellgren-Lawrence (KL) grading assignment is ordinal; therefore, a harsher penalty is provided for misrepresentation with a larger gap between the anticipated and actual KL grade. A machine learning architecture is then constructed and extensive tests are performed to demonstrate how texture properties affect diagnostic performance. Thermal images are used to determine if they might be used to distinguish between radiographs of diseased and healthy knees. The outcomes of machine learning features and manually extracted features are compared. Finally, a stacked model that

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combines second-level machine learning with predictions of patellar texture and clinical characteristics is provided.

Keywords: Osteoarthritis, Thermal images, Knee bone, Feature extraction, yolov2

1. Introduction

One of the most prevalent degenerative diseases affecting elderly people worldwide is knee osteoarthritis (KOA) [1]. Millions of people throughout the world suffer with osteoarthritis, the most common kind of arthritis. It can limit a person's mobility, impact everyday activities, and possibly lead to early retirement (Lespasio, M., 2017). By 2050, this type of degenerative joint disease problem would impact at least 130 million individuals worldwide, 40 millions of whom will be seriously crippled by it, according to Lim, K. Lau, C. S. (2011). KOA occurs when the protective cartilage that serves as a cushion for the ends of bones gradually deteriorates. Any joint can be harmed by osteoarthritis, although the hands, knees, hips, and spine joints are the most frequently impacted. Osteoarthritis symptoms may usually be controlled, despite the fact that the damage to the joints cannot be repaired. Exercise, maintaining a healthy weight, and receiving some therapies may slow the progression of the condition and aid in pain alleviation and joint function. Furthermore, when the disease is in its last stage, the only option for treatment is a total knee replacement. In order to prevent knee surgery, it is advised to diagnose knee osteoarthritis in its early stages. The diagnosis of KOA is determined by a number of factors, knee pain being the first to be examined.

Radiographic grading [3] based on Kellgren-Lawrence grade contributes to this field by developing new machine and deep learning algorithms that aid practitioners in making more accurate diagnoses, prognoses, and decisions. However, two approaches have been used in this field: studies that used clinical data and studies that used imaging data to detect KOA. Imaging software is frequently referred to be a "black box" that produces results without providing any context, but clinical data-based diagnosis is inexact. Because of this, automated KOA severity classification and identification using clinical and imaging data may improve task performance.

The existing methods show that more than 80% of arthritis cases that have an impact on people's quality of life are caused by knee osteoarthritis. It is crucial to recognise it at an early stage to stop its progression because it is an irreversible condition for which the only treatment is knee replacement. With the aid of machine learning algorithms, this study seeks to increase the diagnosis of knee osteoarthritis at all stages using the Kellgren-Lawrence scale.

The main goal of the research is to,

- Develop a machine learning model
- Define diagnostic performance based on illustrations of the texture characteristics (thermal images)
- Compare the outcomes of features extracted manually and through machine learning.

To perform the above-mentioned process, the study aims in developing a stacked model combining the thermal and the clinical features predictions with the 2nd level machine learning architecture.

2. Related Works

Study [1] employed a vote system to determine which features are the best using a variety of algorithms, including Random Forest, Pearson Correlation, Chi-squared, recursive Feature Elimination, Logistic Regression classifier, and Light Gradient Boosting. The best approach in the study [2] was found to be Random Forest, which has 84.3% accuracy when utilizing the features. However, as more variables were included, the model's performance decreased. The outcomes of [3] demonstrated that logistic regression produced 78.3% accuracy with 164 characteristics for left leg, whereas SVM produced 77% accuracy for right leg with 88 characteristics, which was found to perform better. DNN showed 79.39% accuracy which was 50% more when compared to the other algorithms [4].

3. Proposed Work

This study examines the application of transfer learning to automatically identify the knee joint in thermal pictures and contrasts the findings with those of other methods already in use [4]. The study proposes a reliable technique that increases the amount of image data that can be transmitted to a higher-level analysis for computer-aided diagnosis of knee OA. This is significant since deep learning techniques need a lot of data to work successfully and the amount of data available for use in these investigations is small.

To create the final set to be used for the study, some exclusions were performed. In the analysis for a given visit, a knee that was specifically noted (for instance, missing data or low quality) is not accounted. For instance, if a patient underwent treatment on the right knee after visit number two, this method included images of both right and left knees from visits v0, v1, and v2, but excluded only the left knee's images from all subsequent visits. Since the subsequent research would entail estimating jsn and osteophytes, this approach also performed osteophyte grading, and it only excluded fewer than 10% of all samples. Additionally, if the knee was missing from the visit or if the matched PA and lateral views were not present, the knee was not taken into consideration for that visit.

If more than one image for a given view is available from the same patient visit, one is chosen at random. This study's final dataset included 9739 evaluations for 2802 patients. Data for 18053 knee appearances with 9739 PA, 9239 left lateral, and 9264 right lateral images were obtained as a consequence. Patients were divided into non-overlapping training, validation, and subsets. 1000 labeled knee thermal images, with 500 annotated as “Normal” and 500 as “Osteoarthritis” were fed into the model to test the first system. Later, 1500 labeled knee X-ray images, with 500 annotated as “Normal,” 500 as “Non-severe,” and 500 as “Severe,” were fed into the model to test the second system. This study was performed using a dedicated deep learning server with a 64-bit Ubuntu 16.04 operating system and a library based on the CUDA 10.1 toolkit and cuDNN v7.5.0.

The model automatically located the knee lesions and regions of interest of each knee in the radiographic images, depicting a rectangular bounding box during the analysis. An intersection of union of 0.5 between the predicted detection and manually labeled bounding box was used as the threshold to determine whether the predicted bounding box represented the actual class. A value less than the threshold was considered as a false positive.

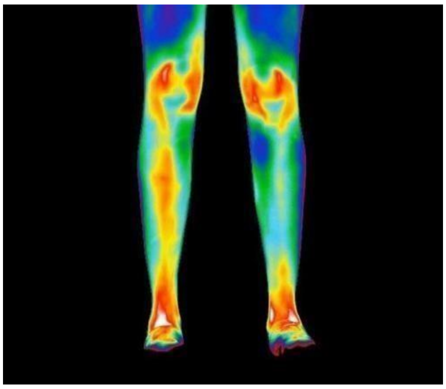

Figure 3.1. Thermal Image Depicting Knee Osteoarthritis

3.1.Dataset and Pre-Processing

Only the knee joint regions that are divided into the right and left joints were cropped in this dataset, after it was retrieved from the oai14,15. The US National Institutes of Health supported the multicenter, longitudinal, prospective observational investigation on knee OA. It offers a freely accessible database describing the evolution of knee osteoarthritis, complete with materials like knee x-rays and magnetic resonance scans [5]. In the current study, 4796 men and women between the ages of 45 and 79 participated.

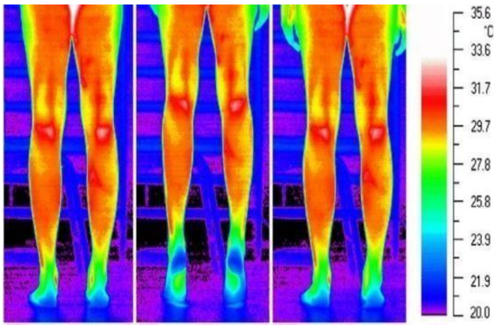

Figure 3.2. Knee Osteoarthritis Thermal Image Dataset [16]

Only trained and certified readers in each participating medical center were involved in classifying the radiographic images. According to the KL classification 1, the radiographic manifestations of the patients were primarily described in terms of osteophytes, joint space narrowing, and subchondral bone alterations such subchondral bone sclerosis and subchondral bone cysts [6].

3.2.Data Augmentation

Prior to training the model, multiple data augmentation techniques were implemented to improve the generalization capabilities of the model.

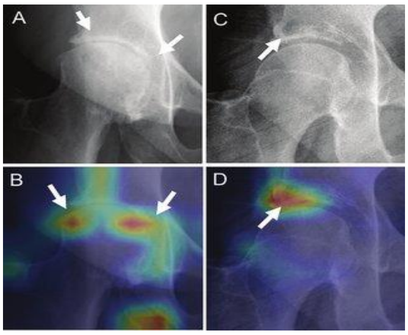

Figure 3.3. Data Augmentation Thermal Image of Knee Osteoarthritis

This was conducted to increase the variation of the dataset in an attempt to imitate the real- life scenario in which the qualities and parameters, such as exposure and orientation, are not consistent.

The techniques applied are as follows:

- Rotation of the image with the value ranging from −3 to 3 degrees varying at every 45 degrees.
- Adjustment of the brightness and contrast by multiplying all pixel red, green, and blue values by seven steps ranging from 0.6 to 1.0.

3.3 Yolo Architecture

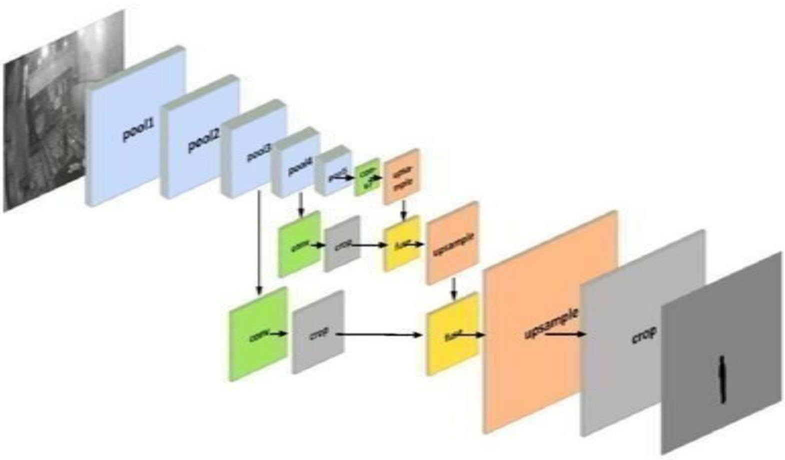

Figure 3.4. YOLO Architecture [17]

The acronym You Only Look Once (YOLO) means "You only look at the image once". This phrase describes the human visual system's capacity to quickly identify items. YOLO is commonly used in object recognition utilizing deep learning. Deep learning is becoming increasingly significant in a variety of applications. The YOLO algorithm, which aims to detect objects quickly and accurately, was originally introduced in 2016. With this technique, a new structure for object recognition systems was introduced. Numerous YOLO variations have been put into practice due to the considerable attention it has received.

3.4 Classification

The process of finding items is typically divided into many steps using traditional methods. To extract the appropriate image features or feature extraction, a convolutional neural network, quicker R-CNN for instance, is employed [9]. Then the output in the form of the feature map is given an input to another neural network, the task of which is to suggest image regions where objects may be located. A network of this type is referred to as a Region Proposal Network (RPN), and it functions as both a classifier (indicating the likelihood that a given region includes an object) and a regression model (descripting a region of an image containing a probable object). The third neural network receives the output of the RPN and is tasked with predicting classes of objects and bounding boxes. Therefore, it is a difficult, multi-step process that must take a while—at least in comparison to YOLO.

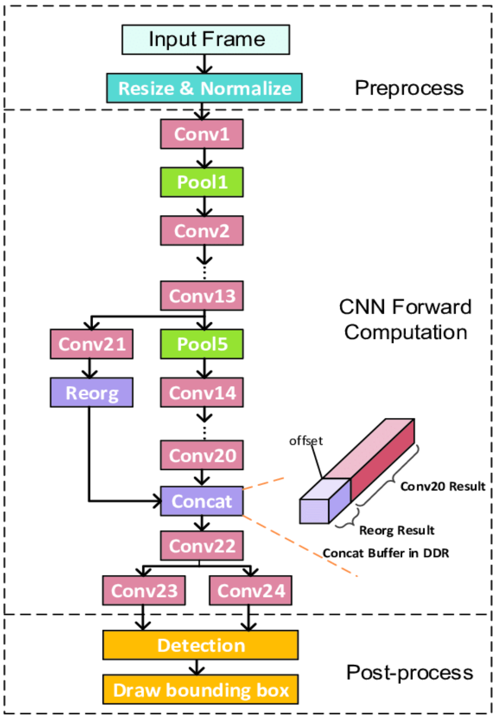

Figure 3.5. YOLO Functional Chart

YOLO takes a completely different approach. At first, it treats the detection and classification problems as a single regression problem. It does not divide the analysis into stages. Instead, a single convolutional neural network simultaneously predicts multiple bounding boxes and determines the class probabilities for each of the areas in which the object has been detected.

4. Results and Discussion

All participants with surface skin temperature measurements had warmer skin on their ventral side, which was likely caused by the anatomical connections between the skin and the circulatory system. The mean surface skin temperature also revealed a statistically significant difference between the groups that were examined, being highest in rheumatoid arthritis patients, lowest in osteoarthritis patients, and lowest in healthy people. Compared to participants with rheumatoid arthritis and healthy subjects, patients with osteoarthritis had narrower temperature distribution curves [10].

Figure 4.1. Threshold Segmentation Thermal Image of OA Patient

In comparison to persons with osteoarthritis and healthy subjects, the temperature distribution curves of rheumatoid arthritis patients have been moved upward [11].

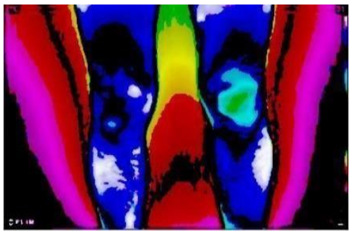

Figure 4.2. Temperature Distribution Thermal Image of OA Patient

Given that the study participants were hospitalized and receiving anti-inflammatory medication as usual, it would be fascinating to compare the drug-naive participants.

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Figure 4. 3. Maximum Threshold Thermal Image of Temperature Distribution

In this study, thermographic imaging has been shown to be a possible straightforward, effective, and repeatable tool for differentiating between healthy people, arthritic subjects, and subjects with osteoarthritis [12].

Figure 4.4. OA Segmented Threshold Image

Table 4.1. Accuracy Achieved by Different Methods

ALGORITHM	ACCURACY	FI SCORE	LOG LOSS
Yolo V2	94.8	0.95	0.6
Logistic regression	84.3	0.89	3.09
KNN	81.11	0.93	0.99
Random forest	78.3	0.91	2.087
SVM	77.7	0.78	1.90
CNN	75.28	0.91	2.89

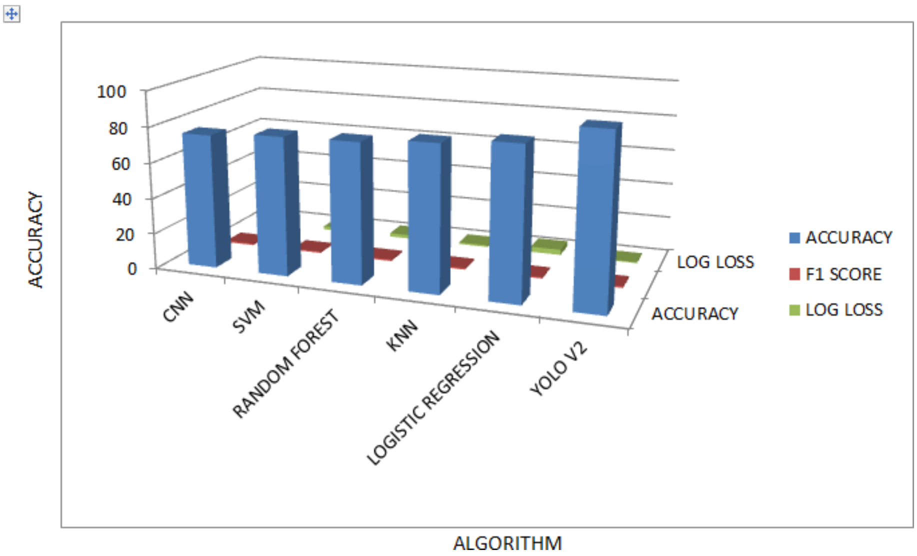

Figure 4.5. Performance Analysis

The F1 score and accuracy obtained by the YOLO v2 is better than all the other architectures, as shown in the above graph [14, 15].

5. Conclusion

A fusion system for predicting the severity of knee osteoarthritis using the deep and the machine learning has been presented in this research. With the help of patient data, ensemble models of YOLO are trained to predict each disease degree according to the Kelgren Lawrence scale. The transfer learning models used to complete the similar job using x-ray images of the knee were densenet201 and inception ResNet. The use of these two forms of data is the primary distinction among conventional and the proposed approach. The results obtained from the current work shows greater performance when utilizing the suggested model than when using a single model. Across all levels, deep learning fed with thermal pictures is more effective at severity prediction of knee osteoarthritis. However, adding details of the patient makes it possible to pinpoint elements that affect how the disease develops, which is crucial for medical professionals to provide a complete diagnosis. Although the suggested methodology helps in disease prediction, there are several drawbacks to consider. One such limitation is that all records of the Americans who participated in the OAAI study were used to run the models on a single dataset. Additionally, the only data used in this work is from the study's baseline.

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