Hybrid neural network for non-image-based knee osteoarthritis prediction

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Abstract

Osteoarthritis (OA) of the knee is a common degenerative joint condition that adversely affects millions of people worldwide. Early detection and forecasting risks of knee OA can help with prompt interventions and individualized treatment plans to slow the disease’s progression. 2 million patients’ worth of Taiwanese data was sampled (2001–2015). 1,068,464 comprised control subjects, while 132,594 patients had Knee Osteoarthritis. Over the course of a three-year period, we sequentially used diagnoses, medication, age, and sex to build a feature matrix. In this study, we developed a risk prediction model using a hybrid strategy (CNN-FFNN) that combines a convolutional neural network (CNN) and a feed-forward neural network (FFNN). The performance of the hybrid approach is also evaluated using a variety of performance indicators. Age and sex were excluded from the list of significant disease variables, and drugs like antacids, cough relievers, and stimulants demonstrated discriminative efficacy. The proposed methodology may help medical personnel identify people who are most at risk of getting knee OA, allowing for preventative measures and individualized treatment regimens to lessen the impact of this crippling ailment.

Keywords: osteoarthritis, knee joint, risks, early detection, hybrid strategy

1. Introduction

The pathologic changes in the osteochondral unit, composed of subchondral bones, the meniscus, and cartilage, are the hallmarks of knee osteoarthritis, a degenerative condition (Saravi et al 2022). It is the cause of about 85% of osteoarthritis’s burden. Knee Osteoarthritis is more common in older people in Taiwan than in any other country, affecting about 37% of people over 50. In contrast, in the US, Knee Osteoarthritis has been observed in 13% of girls and 10% of men 60 years of age or older, adults 65 years of age, and adults (Sebro et al 2022). Age is among the main aetiologies for Knee Osteoarthritis, and it may be linked to cumulative access to much different etiology, which can cause structural changes in the joints. Additional pathogenic signs of Knee Osteoarthritis include the presence of women, obesity, and injuries (Shah et al 2021). According to earlier research, high-impact sports, heavy lifting, and repetitive kneeling are all linked to Knee Osteoarthritis.

Additionally, genetic factors may contribute to roughly 40–80% of the risk of Knee Osteoarthritis, which is more than the risk for hand and hip osteoarthritis (Ciliberti et al 2022). Even long-term use of oral N-acetylcysteine (NAC) medication delivery is linked to an increased risk of Knee Osteoarthritis. Although it remains difficult, forecasting the risk of Knee Osteoarthritis could be done by using artificial intelligence. Recent studies have demonstrated the enormous potential of deep learning (DL) and extensive clinical information to provide personalized healthcare through risk prediction to boost the effectiveness and efficiency of prevention. Managing large-scale data, such as photographs and sizable EMR, uses DL development of conventional statistics methods (Sukkar et al 2022).

The CNN, a sort of DL technique, can examine generic tasks with extreme variability exhibited in the visual data; significant computing tasks, such as object recognition, the categorization, and the segmentation of images, can be carried out using the DL architecture CNN, which is very frequently used. The building blocks that makeup CNN are similar to filters, which can use convolution to separate the pertinent features from the sequential incoming data. CNN was also able to effectively pinpoint a target and its placement of other elements in a picture by capturing the spatial properties of the image (Clark et al 2020). The alternative DL approach uses a Feed Forward Neural Network (FFNN) with triple levels: concealed, output, and input. Incredibly interconnected neural networks called Feed Forward Neural Networks (FFNNs) has the ability to process input in simultaneously and comprehend format. The learning of complex non-uniform input-output correlations is made possible by FFNNs. Furthermore, most prior relevant studies only employed image-based information to identify the risk of Knee Osteoarthritis, not cohorts of EMR or time sequence. DL has been applied to chronic disorders like cancer and
cardiovascular disease, relying on nonimage EMRs rather than using photos to train it for Knee Osteoarthritis risk prediction (He et al. 2022).

Wang et al (2021) suggested a novel learning method that divides the information into two sets in real-time based on their reliability. Additionally, to assist CNN in learning appropriately from the two sets, we build a hybrid loss function. We focus on typical samples using the suggested method, and we manage the effects of cases with low confidence. The five-class task and the early-stage OA task are both the subject of experiments. Wassan et al (2021) proposed scoping assessment of publications utilizing DL methods to forecast major aging-associated diseases, including related to age macular degeneration, cardiovascular and breathing disorders, arthritis, Alzheimer’s disease, and lifestyle factors related to disease development. DL publications on typical aging-related concerns released between the beginning of 2017 and Aug 2021 are searched using Google Scholar, IEEE, and PubMed. These publications were examined, reviewed, and the conclusions were compiled. Akgun et al (2021) summarize current radiopharmaceuticals and how they treat various diseases.

Additionally, theranostics is outlined. In conclusion, researchers in this field may find this review helpful. In this article, they provide a Dempster-Shafer theory (DST)-based multi-modal data fusion paradigm that is evidence-aware. There are three branches in the backbone models: an image branch, a non-image branch, and a fusion branch. The extracted characteristics are inputted into an evidence network for each unit, which generates an evidence score for each chapter that is intended to indicate the accuracy of the result from the existing branch. Alexopoulos et al (2022) examined how MRI and patient data affect the estimation of the incidence of knee OA. Using a series of 600 individuals from the Osteoarthritis Initiative, intermediate-weighted turbo spin-echo (IW-TSE) was used to predict the occurrence of knee OA within 25 months. An U-Net model was built and utilized to part bones on a dual-echo stable state (DESS) sequence to identify an area of interest from the IW-TSE series that contained the knee joint.

![Figure 1 The proposed KOA model's learning curve.](https://www.malque.pub/ojs/index.php/msj)

Tolpadi et al (2020) described a DL pathway to indicate TKR with an AUC of 0.834 0.036 using MRI pictures, clinical data, and demographic data. For patients without OA, the pipeline most impressively means TKR with AUC 0.943 0.057. To discover TKR imaging biomarkers, we also create occlusion images for case-control pairings in test data and evaluate the model's utilization of different locations in each Farajzadeh et al (2023) aimed a deep residue neural network called IIES-OA Net is provided to autonomously assess the seriousness of knee osteoarthritis using radiographs. This is accomplished by calibrating it so that it is concentrated on the distance between the borders of the bones within the knee joint. The IIES-OA Net achieves high average accuracy and average precision while possessing less complexity compared to other approaches, according to experimental results using the datasets. The objective of this work was to develop a machine-learning model based on images for identifying TKA loosening. Lau et al (2022) explained a model for image-based machine learning was created using ImageNet, the Xception model, and a dataset of X-ray images from TKA patients. Then, a new method was developed for creating the medical-information-based neural network model with a random forest classifier, which was based on a dataset of TKA patient clinical parameters. Additionally, the TensorFlow DL framework and Python were used to pre-train the Xception Model on the ImageNet database to forecast loosening.

The following sections make up the remainder of the paper. The method is described in Part 2. The data analysis is in Part 3. The conclusions are covered in Part 4.

2. Materials and Methods
2.1. Dataset

The National Health Insurance Research and Development (NHIRD) of Taiwan, which keeps track of all diagnostic findings, prescriptions, and treatments from approximately 100% of Taiwanese citizens, is one of the most extensive databases for the administration of medical treatment on the planet from which we gathered our data. The National Health Insurance Reimbursement Database (NHIRD) includes information on insurance reimbursement claims, demographic data, Diagnostic and therapeutic ICD-9-CM codes, and prescriptions for drugs with the WHO-ATC codes. From January 1, 2001, to December 31, 2015, we looked at two million data samples. The patient’s informed consent was unnecessary for this study’s approval by the Taipei Medical University Academic Review Board because all data had been de-identified and anonymized.

2.2. Research the people and terminology

Aged 26 or older, with details on gender, age, and at minimum three years of documentation, we identified the Taiwan person database who had at least a single admittance claim between 2001 and 2015, and sufferers who had a bed confinement level code were removed from the study or Before the index date, complete repair of the knee were acceptable treatments for behind cruciate ligament injuries. The initial day when Knee Osteoarthritis was diagnosed is the index date for the Knee Osteoarthritis group. The ICD-9-CM codes, Knee Osteoarthritis localized, or Knee Osteoarthritis unspecified, were used to validate the Knee Osteoarthritis group. The mastery cohort baseline date is the final day the data was accessible. To forecast the likelihood of a Knee Osteoarthritis incidence one year later, we analyzed patients’ EMRs from the previous three years.

2.3. Development of Prediction Systems

To build the feature, we took into account the patient’s highest age, gender, ICD9-CM diagnosis code, WHO-ATC drug policy, and the overall amount of medical checkups discovered throughout the three-year term of monitoring. Additional V-codes were also employed, totaling 1098 ICD-9-CM policy divided into seventeen organ structures (001-999). In this investigation, the ICD-9-CM policy’s first three digits were used. The cohort data included 1029 different diagnostic categories. There are 830 different drug categories contained in the WHO-ATC code, and 695 of those are recommended, according to the group data. The majority of the prescriptions were covered by the initial 5 characters.

2.4. Hybrid CNN and FFNN

It is possible to forecast the likelihood of developing knee osteoarthritis using convolutional neural networks (CNNs) and feedforward neural networks (FFNNs).

Although CNNs are frequently employed for image identification tasks, they can also be used to analyze medical pictures like X-rays or MRI scans of the knees. Convolutional and pooling layers in CNNs are intended to automatically learn and extract significant features from the input images. Then, for jobs requiring classification or regression, these features are supplied into layers that are fully coupled. A CNN could examine knee photos in the context of osteoarthritis prediction and discover patterns that point to the development or risk factors of the condition.

The input, hidden, and output layers are present in the neural network design of FFNNs, on the other hand. A feedforward connection pattern is created when every neuron in a layer is coupled to every neuron in the layer above it. For tabular data, where each input sample is represented by a collection of features, FFNNs are appropriate. The input elements for predicting knee osteoarthritis may include biomarkers, medical history, lifestyle factors, and demographic data. To provide an accurate forecast, the FFNN would learn the correlations between these traits and the likelihood of developing knee osteoarthritis.

Hybrid architecture can benefit from the CNN’s ability to extract pertinent features from complex data and the FFNN’s capability for learning nonlinear relationships and making predictions by fusing the strengths of both CNNs and FFNNs.

A CNN is frequently used as a feature extractor, and the recovered features are then fed into an FFNN for additional processing and decision-making. The FFNN layers can then learn to classify or regress based on these extracted characteristics. The CNN layers can remove high-level visual features from photos or other grid-like input.

Depending on the task, a hybrid CNN and FFNN may have a different architecture and design. It might entail changing the number of layers, the CNN’s filter size, the FFNN’s layer count, and the activation functions applied.

To tackle the prediction of the risk label for knee osteoarthritis, we approached it as the issue of bi-categorization and developed a supervising CNN and FFNN training model. An image-like matrix was created from the EMR input for each patient. We also provided information on the time dimension. The codes for diagnoses and drugs are listed on the input matrix’s vertical axis. Each cell in the diagram represents the patient’s visit history. The horizontal axis comprises 3 years, and Each visit consists of a diagnostic policy for each week split by 7 and a pharmaceutical code for each week divided by 28. The convolution phases, median pooling, maximal pooling, leak rectified linear unit (ReLU), and flattening make up the EMR matrices data input to network design employing CNN. The FFNN architecture receives the patient’s maximum age and sex
values, which are merged to determine the categorization result. All patient data were divided into two groups: 85% for training and 15% for testing, followed by 70% for learning and 30% for internal validity in the training set.

3. Results

The Knee Osteoarthritis group had 83,111 females and 49,483 males, with a mean age and standard deviation of 64.20 and 12.49 years, respectively (Table 1). With 545,902 females and 522,562 men, the mean age of the non-knee osteoarthritis control group was 51.0015.79 years. The average number of medical checkups per sufferer per year in the groups with knee osteoarthritis and those without it was 38.50 and 21.90, respectively. In the Knee Osteoarthritis group and the non-Knee Osteoarthritis mastery group, the yearly average number of diagnoses per patient was 34.60, while it was 21.90 in the non-Knee Osteoarthritis group. In the Knee Osteoarthritis and mastery groups, the average number of prescriptions per sufferer per year was 30.54, while 62.11 were seen in the Knee Osteoarthritis group. If we multiply the number of medications by the number of prescription days each patient receives each year, In the Knee Osteoarthritis cohort and the mastery cohort, we discover, respectively, 694.81 and 298 drugs per sufferers. In the mastery cohort and Knee Osteoarthritis cohort, there were similarly 1.90 and 0.82 drugs per sufferer per day, respectively. Based on the Knee Osteoarthritis model’s learning curve employing diagnoses and pharmaceutical characteristics (Figure 2), the validate and learning losing line demonstrates that it has been shown that the Knee Osteoarthritis technique is less prone to excessive matching. A minor gap formed between the plots of learning loss and verification failure, which both decreased to a center of stabilization. The learning losses and verification losses plots, as well as the plots of learning accuracy and efficacy of verification, which rise until they reach a point of equilibrium and have little gaps within them, demonstrate that the training and validation datasets were representative. With ICD-9-CM codes as its only input attributes, the Knee Osteoarthritis model achieved an AUROC of 0.94 at its optimum levels of 0.34 (Table 2). The Knee Osteoarthritis, on the other hand, showed an AUROC 0.79 with the optimal level set at 0.05 when only pharmaceutical (WHO-ATC code) input features were used. The Knee Osteoarthritis demonstrated an AUROC, Particularity, recall (positive predictive value), and precision (positive predictive value) of 0.96, 0.88, 0.92, and 0.8, respectively, at the best threshold of 0.15 while using both WHO-ATC medicines and ICD-9-CM diagnostics as input features (Figure 2). The total risk probability score, which ranged from zero (non-Knee Osteoarthritis) to one (Knee Osteoarthritis), allowed us to find the best balance between the true positive ratio and the false positive ratio. By severing some links between nodes inside layers, we used the TensorFlow optimization toolbox to improve the Knee Osteoarthritis model (Figure 3). After optimization, the model’s size was drastically reduced from its initial (442 MB) by up to 33% (147 MB). The AUROC between the initial and optimized models was discovered to be very similar.

Table 1 Population of the collected Data.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Mastery cohort (n=1,068,464)</th>
<th>KOA Group (n=132,594)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Race/Ethnicity</td>
<td>All Asian Age, year</td>
<td>All Asian</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td>Average</td>
<td>51</td>
</tr>
<tr>
<td>Average</td>
<td>Max</td>
<td>113</td>
</tr>
<tr>
<td>Average</td>
<td>Min</td>
<td>27</td>
</tr>
<tr>
<td>Average</td>
<td>M ±SD</td>
<td>51.01 (±15.78)</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td>Men</td>
<td>523,563 (48.92)</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td>Women</td>
<td>546,903 (51.08)</td>
</tr>
<tr>
<td>Median sufferers yearly accumulation, n/ sufferers /year</td>
<td>WHO-ATC Pharmaceutical values</td>
<td>31.55</td>
</tr>
<tr>
<td>Counting pharmaceuticals (WHO-ATC) days prescribed</td>
<td>297.62</td>
<td>695.82</td>
</tr>
<tr>
<td>Diagnosis (ICD-9-CM) values</td>
<td>23.92</td>
<td>35.61</td>
</tr>
<tr>
<td>Medical checkup values</td>
<td>22.91</td>
<td>39.51</td>
</tr>
</tbody>
</table>

Table 2 The effectiveness of KOA with various input characteristics.

<table>
<thead>
<tr>
<th>Input Features</th>
<th>Diagnoses and medications</th>
<th>Diagnoses only</th>
<th>Medications only</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUROC</td>
<td>0.96</td>
<td>0.95</td>
<td>0.78</td>
</tr>
<tr>
<td>Recall</td>
<td>0.88</td>
<td>0.84</td>
<td>0.64</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.92</td>
<td>0.92</td>
<td>0.82</td>
</tr>
<tr>
<td>Precision</td>
<td>0.80</td>
<td>0.77</td>
<td>0.62</td>
</tr>
</tbody>
</table>

https://www.malque.pub/ojs/index.php/msj
Chronic comorbidities, acute respiratory infections, esophageal, stomach, and duodenal disorders, and a greater illness occurrence in the eyes and adnexa were distinguishing factors for Knee Osteoarthritis prediction. While antacids, cough suppressants, and the most popular were expectorants discriminating characteristics. To compare the performance of the theory, three sufferers from the mastery cohort for people without knee osteoarthritis and those who do were chosen at random according to the comparison of features, especially the abundance of characteristics over three trips (Table 3). According to this investigation, the Knee Osteoarthritis model’s optimum threshold was computed at 0.152, with the highest non-Knee Osteoarthritis score coming in at 0.137 and the least Knee Osteoarthritis score coming in at 0.172. These individuals shared a similar number of characteristics, such as diagnoses and drugs, as non Knee Osteoarthritis sufferers, but their scores differed noticeably.

4. Conclusions

Knee Osteoarthritis was created to focus on vulnerable sufferers of Knee Osteoarthritis and give them a precision preventative program. It achieved great sensitivity and specificity and could have a one-year forecast of the chance of having knee osteoarthritis. Before performing an imaging or biomechanical retrieval screening procedure, based on longitudinal
medical records, Knee Osteoarthritis can assist doctors in identifying patients who have a greater chance of getting Knee Osteoarthritis in the future. There are a few restrictions on this study. The results of MRI or other imaging tests, laboratory findings, physique mass index, exposure (such as occupational exposure), genetic markers, and details on the kinds, pathologic features, and grading of Knee Osteoarthritis were not included in the NHIRD. As a result, distinct Knee Osteoarthritis predictions were not possible. Because it has non-image characteristics, this model can still be used in an overall population anywhere in the universe. To improve the efficiency and detailed tagging result, additional research using picture factors under the same concept will be required.

Ethical considerations
Not applicable.

Declaration of interest
The authors declare no conflicts of interest.

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Reference
Sebro R, De la Garza-Ramos C (2022) Statistically based nomograms for the minimal needle length required to achieve intra-articular fluoroscopic-guided injections of the shoulder, hip, and knee. PM&R.