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Synergizing Generative Adversarial Networks and Pseudo-Labeling for Improved Knee Osteoarthritis Detection

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***Abstract*— Progressive cartilage breakdown and joint inflammation are hallmarks of the common joint disease known as osteoarthritis (OA). The timely intervention and management of osteoarthritis (OA) depend on early detection. However, this can be difficult to achieve because labelled medical imaging data is scarce, and the disease's presentations are complex. A notable skew between the proportion of healthy and OA knee images can be seen in knee OA datasets, a phenomenon known as class imbalance. As a result, the model may underperform on the minority class (OA) and prioritize the majority class during training. The goal of the research is to further the development of more accurate and reliable techniques for knee OA detection. A novel method for knee osteoarthritis detection that first uses ResNet, DenseNet, VGG16, and VGG19 convolutional neural network (CNN) architectures for classification after generative adversarial networks (GANs) for data augmentation and pseudo-labeling is predicted. The aim of the work is to use labeled and unlabeled data to develop the robustness and accuracy of osteoarthritis detection. It is shown via thorough experimentation that the strategy is beneficial in enhancing classification performance, with ResNet obtaining the greatest accuracy and F1 score among the networks we studied. According to the research, pseudo-labeling and GAN-based data augmentation strategies can greatly improve osteoarthritis diagnosis accuracy and clinical significance. This work advances the field of medical image analysis and has potential benefits for bettering osteoarthritis patient treatment. The proposed approach performs well with an accuracy of 96.23%, precision of 0.963, recall of 0.959, and F1 score of 0.9246.**

Keywords*— *Osteoarthritis (OA), Generative Adversarial Networks (GANs), Convolutional Neural Networks(CNNs), Residual Networks(ResNet), Dense Convolutional Networks(DenseNet), Visual Geometry Group Network(VGGNet).

I. Introduction

The most prevalent type of arthritis and a leading global cause of disability is osteoarthritis (OA). It mostly affects the joints, resulting in discomfort, stiffness, and reduced range of motion. Osteoarthritis is frequently linked to aging and usually occurs gradually over time, though obesity or joint injuries can occasionally cause it. Osteoarthritis can cause discomfort, stiffness, edema, and reduced range of motion in the impacted joints [1]. The intensity of these symptoms varies, and they could worsen with time. A person's capacity to carry out everyday tasks and quality of life can be greatly impacted by osteoarthritis. Osteoarthritis treatment aims to reduce pain, enhance joint function, and impede the disease's advancement. A mix of medicine, physical therapy, lifestyle changes, and, in certain situations, surgery may be used to treat this. Osteoarthritis has no known treatment, but people with the illness can live active, satisfying lives by controlling their symptoms and caring for their joints. The tissue covering the ends of the bones in the joint, called cartilage, begins to deteriorate in osteoarthritis, a degenerative joint condition. Over time, bone rubbing on bone can cause the cartilage to deteriorate and cause pain, edema, and loss of joint function.

People who work in jobs or engage in activities requiring frequent joint motions are also more vulnerable. While the exact cause of osteoarthritis remains unknown, it is believed to result from a combination of mechanical, metabolic, and genetic factors. Cartilage serves as a cushion in healthy joints, reducing shock and facilitating smooth joint movement. However, cartilage degrades and becomes less elastic in osteoarthritis, which causes friction between the bones and the development of osteophytes, or bone spurs [2]. A combination of clinical assessment, medical history, physical examination, and imaging tests like MRIs, ultrasounds, and X-rays are used to diagnose osteoarthritis. Blood testing can rule out rheumatoid arthritis and other types of arthritis. Although osteoarthritis cannot be cured, several therapy options can help control symptoms and enhance joint function. Some examples are medication, physical therapy, dietary changes, assistive technology, and, in extreme circumstances, surgery. Grading schemes are frequently used

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in osteoarthritis (OA) to categorize the degree of joint degradation according to radiographic data, such as X-rays or MRI scans. Healthcare professionals can use these grading systems to guide treatment decisions and predict the course of a disease by evaluating the degree of cartilage loss, bone alterations, and joint space narrowing.

One popular technique for radiographic evaluation of osteoarthritis (OA) severity, especially in the knee joint, is the Kellgren-Lawrence (KL) grading system—this grading system, which was created in 1957 by Drs. John Kellgren and Jeffrey Lawrence classify OA according to the degree of structural alterations seen in X-ray pictures. A consistent method for measuring the degree of joint degeneration is provided by the KL grading system, which helps with diagnosis, prognosis, and therapy planning. There are five grades in the KL grading system:

- Grade 0: There are no signs of osteoarthritis on radiographs. There is no sign of cartilage loss or other structural anomalies since the joint space is normal.
- Grade 1: Osteoarthritis with doubt. Minor osteophytes, or bone spurs, could be present, but the joint space is normal or slightly narrowed.
- Grade 2: Mild osteoarthritis. There are distinct osteophytes and possible modest narrowing of the joint space, which are early indicators of cartilage loss.
- Grade 3: Osteoarthritis of moderate severity. Significant joint space narrowing and more noticeable osteophytes indicate mild cartilage degradation and possible bone-on-bone contact.
- Grade 4: Severe osteoarthritis. There are large osteophytes, widespread joint space constriction, and subchondral sclerosis (hardening of the bone beneath the cartilage). Joint deformity and severe cartilage loss could be observed.

Clinicians can assess the course of the disease, choose a course of treatment, and track patient response to treatment using the KL grade. It is crucial to remember that the KL grading system should only be used in conjunction with other clinical examinations because of its limitations, which include subjective interpretation and the possibility of discrepancies between radiographic findings and clinical complaints.

A. Challenges

The expenses related to OA's diagnosis, treatment, and management significantly strain healthcare systems. Medical visits, prescription drugs, imaging tests, physical therapy, assistive technology, and occasionally surgical procedures are included in these expenses. People with OA might need surgery, rehabilitation, and medical consultations more frequently, increasing their use of healthcare resources and lengthening their hospital stays [3]. A comprehensive strategy emphasizing prevention, early detection, patient education, multidisciplinary management, and access to inexpensive, evidence-based interventions is needed to address the effects of OA on people and healthcare systems [4]. The burden of OA can be lessened, and the outcomes for those impacted by it can be improved by strategies that support healthy lifestyle choices, weight control, physical exercise, joint protection, and self-management abilities. Effective management of osteoarthritis (OA) and better patient outcomes depend heavily on early identification. Early OA detection enables prompt therapies targeted at stopping or delaying the disease's progression. Healthcare professionals can put procedures into place to prevent additional joint damage and maintain joint function by identifying people who are at risk or who exhibit early indicators of OA. Early detection can result in financial savings for patients, healthcare systems, and society by stopping disease progression, reducing the need for intrusive therapies, and improving patient outcomes.

The convergence of deep learning and osteoarthritis (OA) offers promising prospects for enhancing this common joint ailment's identification, assessment, and treatment. Clinical decision support, predictive modelling, and medical imaging analysis are just a few medical applications where deep learning, a subsection of AI and machine learning, has shown perspective. Deep learning algorithms can identify and measure changes in joint anatomy, tissue integrity, and bone structure associated with osteoarthritis by analyzing medical images such as X-rays, MRI scans, and ultrasound images [5]. These algorithms help radiologists and doctors diagnose and treat patients accurately by automatically recognizing small irregularities symptomatic of osteoarthritis in its early stages. Even though deep learning has a lot of potential for treating osteoarthritis, there are still several obstacles to overcome, such as the requirement for sizable and varied datasets, strong model validation, results that are easy to understand, and integration with clinical workflows. Translating technology discoveries into real clinical advantages for patients with osteoarthritis and expanding the area of deep learning in that field requires concerted efforts by researchers, doctors, industry partners, and regulatory bodies. The following are the issues that this study aims to address:

- The difficulty of diagnosing knee osteoarthritis in its early stages, when symptoms may be moderate or non-specific, is one major problem. Early detection is essential for starting prompt interventions and therapies to stop long-term joint damage and limit the condition's progression.
- Osteoarthritis in the knee is linked to high medical expenses and patient morbidity. Enhancing detection techniques can ease the strain on healthcare systems and increase cost-effectiveness by enabling early intervention and individualized treatment plans, which can improve patient outcomes.
- Technological developments in computer vision, deep learning, and machine learning present a chance to create novel detection models that take advantage of these tools to improve the precision and effectiveness of knee osteoarthritis detection. Using such cutting-edge technology in clinical settings can completely change how osteoarthritis is identified and treated.

The upcoming part of the document is structured in the following order: Section 2 examines a few previous relevant research; Section 3 offers a methodology; Section 4 shows

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the experimental results along with a thorough explanation of the findings. The study is finally concluded in Section 5, which also addresses future work.

II. Literature Review

This study uses X-ray and MRI data to assess knee morphology's discriminative ability in automatically detecting osteophytes. A deep learning-based model is created to fragment the femur and tibia for the X-ray examination [6]. The models produced stable accuracy values of 0.73, 0.69, 0.74, and 0.74 for FM, FL, TM, and TL, respectively, based on X-ray-based 2D morphology. In that order, stable accuracy using 3D bone morphology from MRI was 0.80, 0.77, 0.71, and 0.76. All the compartments except for TM performed better than in 2D, with the femoral compartments showing particularly notable gains. 2D has the advantage of using less power. This imaging modality is more widely used and accessible, which could result in larger datasets. MRI offers comprehensive three-dimensional data regarding soft tissues, cartilage, and bones. One of the drawbacks of 2D images is their lack of depth, which makes it difficult to fully convey the intricacy of the shape and position of osteophytes, particularly when there are overlapping structures. 3D volume analysis is resource-intensive and demands much more processing power and training time. The study presents a deep learning-based technique using a U-Net model and VGG11 encoder to automatically identify joints and segment bones in knee radiographs. The suggested method can efficiently identify and extract joints from radiography images. It also segments bones accurately, achieving an Intersection over Union (IOU) segmentation mean score of 0.963. The joint space width between the femur and tibia bones can be calculated by measuring vertical distances using an algorithmic method that is introduced [7]. The photos are consistently categorized as either normal or showing osteoarthritis, with an accuracy score of 89%.

This study introduces a 3D CNN model and a semi-supervised multi-view framework for identifying knee OA using 3D MRI data. We present a semi-supervised learning strategy that combines labeled and unlabeled data to enhance the suggested model's interpretation and relevancy. The contributions of the various parts of the proposed structure were examined by ablation research, which shed light on the best way to construct the model. The findings suggest that the method can potentially increase the precision and effectiveness of OA diagnosis. An AUC of 93.20% was reported using the suggested framework for diagnosing knee OA. One advantage is that radiologists can spend much less time segmenting bones by hand when they automate the process. More uniform assessments of bone features can be achieved by AI-based segmentation, which will improve study comparability and treatment tracking. The drawbacks consist of the standard and volume of training data, which significantly impact the accuracy of AI models. This paper introduces an ensemble network that uses a deep learning approach to expect a reliable and precise KL grade for the severity of knee osteoarthritis. Rather than using datasets with one image's size, we trained separate models on knee X-ray datasets using the best image size for each model in an ensemble network [8]. We used an 8260-image dataset from the Osteoarthritis Initiative public dataset to conduct some studies. The suggested ensemble network performed the best, with an F1-score of 0.7665 and an accuracy of 76.93%. The benefit of ensemble approaches is that they can lessen the possibility of overfitting, a phenomenon in which a model performs well on training data but adversely on unknown data. The advantages of several deep learning architectures can be combined using ensembles. The drawbacks of ensemble approaches include managing and training numerous models, which can be more time- and computationally intensive than employing a single model.

This paper suggests a novel method for categorizing knee osteoarthritis using deep learning and a whale optimization technique. Efficientnet-b0 and Densenet201—have been used for the training and feature extraction. Both chosen models were trained using deep transfer learning with fixed hyperparameter values using knee X-ray images. Subsequently, a feature vector with greater information than the initial feature vector is created through fusion utilizing a canonical correlation technique. Subsequently, an enhanced approach for whale optimization is created to reduce dimensionality. The final step involves sending the chosen features to machine learning techniques for classification, like neural networks and SVM [9]. The trials were conducted on the publicly available dataset and attained an accuracy of 90.1%. DNNs provide a more objective method, which can reduce the subjectivity of human diagnosis variability. DNNs can automatically extract pertinent features from X-ray images for OA classification, removing the need for labour-intensive and domain-specific manual feature engineering. DNN training can take a lot of time and processing power, which could be a drawback in some situations. DNNs are vulnerable to overfitting and poor performance on unknown data if the training set is too small or undiversified. Using a solitary posteroanterior standing knee x-ray image, an automated deep learning-based ordinal classification method is used to grade and diagnose knee osteoarthritis in the early stages [10]. Important characteristics of osteoarthritis (OA) include narrowing of the joint space, the development of osteophytes, and bone sclerosis, which can be seen on X-rays and can help with diagnosis and severity categorization. Only two dimensions are shown on X-rays, leaving out depth information about soft tissues like cartilage, which is important in osteoarthritis. It may make it difficult to distinguish OA from other medical conditions. X-rays may not be sensitive enough to identify soft tissue changes in early-stage OA, which may occur prior to notable bone changes. The model's overall performance is enhanced by combining transfer learning with refined ResNet-34, VGG-19, DenseNet 121, and DenseNet 161. With a 95% confidence interval and an overall accuracy of 98%, the proposed technique yielded a 0.99 Quadratic Weighted Kappa.

The proposed models are split into two frameworks that use transfer learning (TL) to refine the pre-trained convolutional neural networks (CNNs) and use them for feature extraction. Furthermore, a conventional machine learning (ML) classifier utilizes the improved feature space to improve knee OA classification enactment. The pre-trained CNN from the first context was fine-tuned using the notion of

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TL to fit the two classes, three classes, and fd classes-based models in the second framework, which made minor modifications to the processes in the first framework [11]. Grading OA severity more accurately can be possible when DL is used for feature extraction and ML is used for classification, compared to just one technique. It may be computationally more economical to use pre-trained DL models for feature extraction rather than building an intricate DL model from the beginning for both feature extraction and classification. Compared to a single approach, this one may need more development time and demand skills in both DL and ML. The experimental data demonstrated performance enhancement with fewer multiclass labels, with binary class labels surpassing all others, achieving an accuracy rate of 90.8%.

Generative Adversarial Networks (GANs) and pseudo-labeling approaches can greatly improve patient outcomes in knee osteoarthritis identification. The following are some ways to put this approach into practice to enhance patient outcomes:

• Increase Precision in Diagnosis: Create fake knee joint images to enhance the dataset, giving the detection model a more diverse training set. It lessens overfitting and increases the model's capacity to generalize to new data, which helps to improve the accuracy of diagnosis of knee osteoarthritis.

• Address Imbalance in Data: GANs can produce more images for classes that are underrepresented, so the training dataset is balanced. It contributes to developing a model that works well in all classes, including uncommon or early knee osteoarthritis cases, resulting in more accurate and consistent diagnosis.

• Promote Early Detection and Intervention: GANs and pseudo-labeling improve diagnostic capacity, making identifying knee osteoarthritis in its early stages easier. It is important for early intervention. Improved patient outcomes and a slower rate of illness development can result from early diagnosis and more effective treatment approaches.

• Efficient Use of Medical Resources: GANs and pseudo-labeling work together to maximize the use of medical resources by increasing diagnostic accuracy and lowering the requirement for additional diagnostic tests. It leads to cost savings and more efficient use of healthcare services

III. Proposed Model

Osteoarthritis (OA) is a chronic degenerative joint condition that leads to pain, stiffness, and impaired joint function due to the slow destruction of cartilage. This article presents a unique approach that combines pseudo-labeling approaches with Generative Adversarial Networks (GANs) to improve osteoarthritis detection. Strong deep learning models called generative adversarial networks (GANs) may produce realistic synthetic images that closely mimic genuine medical imaging [12]. The goal is to create fake images that depict the many manifestations of osteoarthritis, such as differences in joint structure, bone morphology, and cartilage deterioration, by training GANs on labeled data of existing knee joint images. Then, to enhance the labeled dataset, the artificial images produced by the GANs are combined with pseudo-labelling methods. Pseudo-labeling is a semi-supervised learning technique in which the model uses its predictions to label unlabeled data [13]. We aim to produce a more comprehensive and varied dataset to train a discriminative model for osteoarthritis detection by merging the labeled data with the pseudo-labeled data produced by the GANs. Using labeled and pseudo-labeled samples, the discriminative model is trained on the combined dataset to increase detection resilience and accuracy. We hypothesise that the discriminative model will be more proficient in recognizing the complex characteristics of osteoarthritis and distinguishing between healthy and diseased joints. The detection model is built, and its efficiency in handling image data is assessed. Fig. 1 shows the workflow of the proposed method.

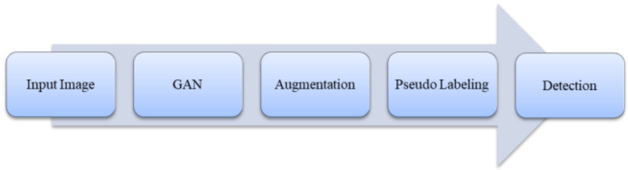

Fig. 1. Workflow of the proposed methodology

A. Knee Osteoarthritis Dataset

The Osteoarthritis Initiative (OAI) dataset is one of the most popular datasets for knee osteoarthritis studies. The OAI dataset comprises clinical, radiographic, and MRI data from hundreds of people, providing a comprehensive longitudinal data collection on knee osteoarthritis. X-rays and other radiographic images can be used to evaluate the knee's degree of osteoarthritis and the joint's anatomy [14]. Researchers can use these images to assess characteristics, including osteophyte formation, aberrant alignment, and joint space narrowing. Research on knee osteoarthritis has advanced greatly because this dataset has made it possible to examine treatment outcomes, risk factors, and the course of the illness. The dataset contains comprehensive clinical data, including self-reported measures of knee pain, function, and quality of life, demographics, medical history, and physical examination results. The dataset comprises 8260 left and right knee X-ray images with posterior-anterior (PA) fixed flexion. An overall of 4796 participants, encompassing both male and female patients aged 45 to 79, were used to create these images. Following a 7:1:2 ratio, the original dataset comprises 1656 images in the test set, 826 in the validation set, and 5778 in the training set. Fig. 2. Shows sample input images for each grade.

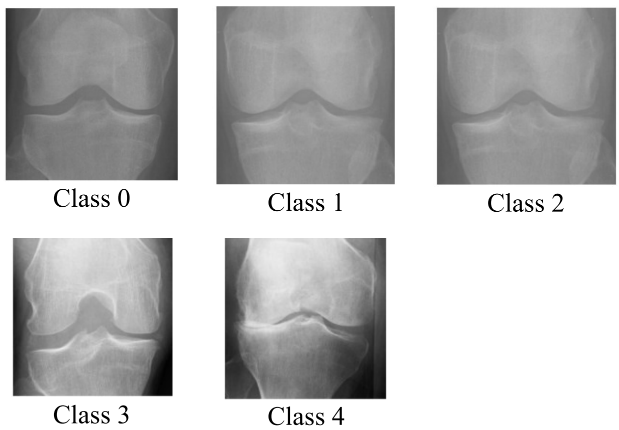

Fig. 2. Sample Input Images

B. Preprocessing

Pre-processing is vital in preparing medical imaging data for analysis and model training. When generative adversarial networks (GANs) and pseudo-labeling are used to detect osteoarthritis, pre-treatment ensures that the input data is

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standardized, normalized, and devoid of artefacts that could impair the detection model's performance. Z-score normalization [15] is a popular method for altering data with a mean of 0 and a standard deviation of 1. Z-score normalization is used in medical imaging to equalize the intensity levels of pixel values across several images or scans, including using GANs and pseudo-labelling to identify osteoarthritis. Subtract the mean intensity (μ) from the initial pixel value for each pixel in the image, then divide the result by the standard deviation (σ) as shown as in (1). This technique standardized the intensity value concerning the dataset's mean and distribution of intensity levels.

$$Z - score\ normalization = \frac{Original\ Pixel - Mean\ Intensity}{Standard\ deviation\ of\ intensity} \quad (1)$$

C. Generative Adversarial Network

In medical imaging, obtaining huge datasets is difficult owing to logistical and ethical issues. GANs are especially useful for producing realistic fake medical images of knee joints. The accuracy of knee osteoarthritis identification is increased by using this enhanced dataset to build more reliable and broad models. Class imbalance can be addressed, and the model's performance can be guaranteed throughout the disease's progression using GANs to provide more samples for underrepresented classes. Complex patterns in knee osteoarthritis images that may be challenging to model using conventional techniques can be learned and captured by GANs. The generator and discriminator are the two primary parts of a Generative Adversarial Network (GAN) that must be trained. The discriminator distinguishes actual and fake data, while the generator creates fake data. Both components improve repeatedly through adversarial training: the discriminator becomes more proficient at distinguishing real data from fake, while the generator produces real data [15]. GAN training aims to get the generator G to approach the genuine data distribution Pdata(x) by teaching it to create fake data samples from a latent space distribution p(z). Using a loss function like the Jensen-Shannon divergence or the Wasserstein distance, the generator is trained to reduce the variance between the generated Pgen(x) and genuine data distribution. Simultaneously, discriminator D undergoes training to distinguish between genuine data samples x derived from the genuine data distribution and fake data samples G(z) produced by the generator. The discriminator seeks to minimize its classification error by optimizing its capacity to distinguish between authentic and fraudulent samples. It is possible to describe the adversarial training process as a minimax game in which the discriminator maximizes its loss, and the generator reduces its loss.

$$min_G max_D V(D, G) = E_{x \approx P_{data}(x)}[\log D(x)] + E_{z \sim P(z)}\left[\log\left(1 - D\left(G(z)\right)\right)\right] \quad (2)$$

The discriminator's loss in properly classifying real data is represented by the first component in this objective function, while the second term represents its loss in wrongly categorizing produced data. While the discriminator seeks to exhaust the possibilities of the objective function by precisely differentiating between actual and fake samples, the generator seeks to decrease the second term by enhancing the quality of the samples it generates.

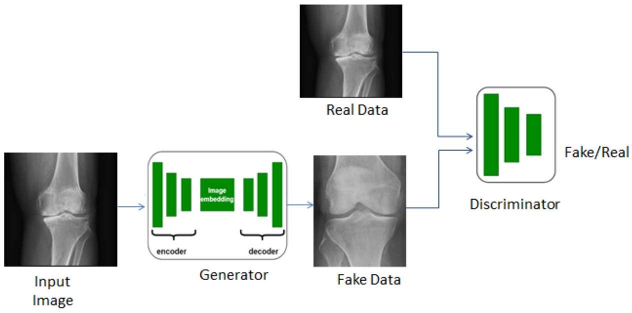

Fig. 3. Working of GAN

The generator and discriminator arrive at a Nash equilibrium through iterative training, where the generator produces real data that is undetectable from genuine data, and the discriminator cannot consistently discern between real and fake samples [12]. Through this adversarial training process, the GAN can understand intricate data distributions and produce fake samples The GAN can understand intricate data distributions and produce fake samples through this adversarial training process. Fig. 3. Shows the working of GAN.

D. Augmentation

A key tactic for improving the efficacy of deep learning model training is to augment the dataset with synthetic images, especially for applications like osteoarthritis identification from medical imaging data. A Generative Adversarial Network (GAN) is used in this procedure to produce artificial images that closely resemble photographs of osteoarthritis. The generator part of the GAN learns to generate images that resemble real medical scans, complete with bone anomalies, cartilage deterioration, and joint deformities, through adversarial training [16]. After that, the original dataset is joined with these artificial images to produce an augmented dataset with a wider range of samples. Researchers want to progress the sturdiness and generalization capacity of the osteoarthritis recognition model by adding more diversity and complexity to the training data by enriching the dataset with fake images. The model's ability to detect osteoarthritis from medical images is improved by this augmentation procedure, which also makes the model more resilient to changes in imaging circumstances, disease symptoms, and patient demographics. To guarantee the dependability of the augmented dataset for model training, validation and quality control procedures are usually carried out to ensure the synthetic images correctly capture relevant osteoarthritis aspects and retain consistency with real medical images.

E. Self-supervised Psudo-labeling

Self-training, or pseudo-labeling of unlabeled data, is a semi-supervised learning strategy in which unlabeled data is labeled according to a trained model's predictions. This method uses the model to predict labels for the unlabeled data samples after training on a small labeled dataset [16]. The training dataset is essentially expanded by adding these pseudo-labels to the original labeled data and using them in conjunction. The following is a mathematical representation of pseudo-labeling:

Let $D_L = \{(x_i, y_i)\}$ represent the labeled dataset, where x_i represents a data sample and y_i its corresponding true label.

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Let $D_U = \{x_i\}$ represent the pool of unlabeled data samples. After training the initial model M on D_L, pseudo-labels $\hat{y}_i$ are assigned to the unlabeled samples x_i based on model predictions as in (3).

$$\hat{y}_i = \mathrm{M}(xi) \qquad (3)$$

The pseudo-labeled samples $\{(x_i, \hat{y}_i)$ are then added to the labeled dataset D_L to create a composite dataset $D_C = \{(x_i, y_i)\} \cup \{(x_i, \hat{y}_i)\}$ The model's parameters are then simplified by retraining it on the expanded dataset. During several epochs, the model iteratively improves its predictions and gains knowledge from the larger dataset. When obtaining labeled data is costly or limited, pseudo-labeling efficiently utilises the information in the unlabeled data to enhance the model's performance. To stop the spread of false labels and guarantee ongoing learning efficacy, it is crucial to closely check the eminence of the pseudo-labels and track the model's performance during training. Fig. 4. Shows working on pseudo-labeling.

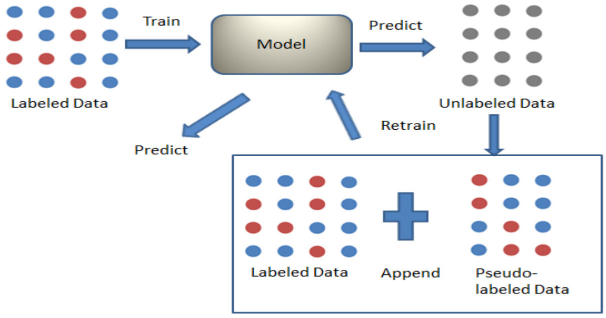

Fig. 4. Working of pseudo-labeling

F. Detection

The augmented dataset, which consists of both the original labeled data and the pseudo-labeled data produced by methods like pseudo-labeling or self-training, is used to enhance the parameters of the detection model during training. Through this procedure, the detection model can learn from a larger and more varied collection of samples, improving the model's ability to diagnose osteoarthritis from medical imaging data accurately. Osteoarthritis in medical imaging data can be detected using various detection models, and we compare the performance.

- **Residual Networks:** ResNet-101 architectures are often used for image classification applications [17]. The vanishing gradient issue is partially resolved by residual connections, which makes it possible to train deeper networks efficiently.
- **Dense Convolution Networks:** DenseNet-161 topologies allow for feature transmission and reuse by dense layer connections [18]. DenseNet models are renowned for their robust enactment of image classification errands and effective parameter usage.
- **VGG16:** As a deep convolutional neural network architecture, VGG16 can be applied to the detection of osteoarthritis using medical imaging data of the knee [19]. VGG16 can be used in various fields, including medical imaging, because it can extract hierarchical features from images.
- **VGG19:** VGG19 can identify osteoarthritis from medical imaging data, such as knee X-rays [20]. The deeper layers of VGG19, an extension of VGG16 architecture, consist of 16 convolutional layers and three fully connected layers.

IV. Results and Discussion

The X-ray radiographs that we obtained from the OAI library were used. There are 4796 participants in the photos, both men and women. Since the work primary focus is on the KL grades, radiographs from the baseline cohort with annotated KL ratings are obtained to evaluate the work. The dataset consisted of 8260 radiographs, including left and right knee images. Table 1. shows the dataset used for training and testing the system for each grade.

Table 1. Dataset Composition

Dataset	Total Number of Images	KL Grade	Number of Images
Training Set(Training and Validation)	6604	0	2615
		1	1198
		2	1729
		3	862
		4	200
Test Set	1656	0	638
		1	297
		2	448
		3	222
		4	51

The learning rate, which regulates the step size during optimization and usually varies from 0.0001 to 0.001 for both the generator and discriminator, is one of the important hyperparameters for the GAN component. The number of samples processed before the model's parameters are changed is determined by the batch size, which is set at 32. Furthermore, the latent space dimension is often between 100 and 200, affecting the resulting images' complexity. The trade-off between adding noisy labels and growing the training set is typically balanced by using a threshold of approximately 0.9 to guarantee that only high-confidence predictions are pseudo-labeled. The proportion of actual labeled data to pseudo-labeled data is also crucial since the right balance between noisy and non-noisy pseudo-labels can improve learning without overloading the model. Fine-tuning variables like the number of attention heads and the dimensionality of the attention layers is necessary for integrating attention mechanisms. These parameters increase detection accuracy by assisting the model in concentrating on the most important aspects of the knee joint images. Knee osteoarthritis detection models can be made much more effective by carefully adjusting these hyperparameters, combining the synergistic effects of GANs and pseudo-labeling to improve patient outcomes and diagnosis accuracy. A GAN model's accuracy can be greatly impacted by its hyperparameters, which include the learning rate, batch size, and number of training epochs. The best values for these hyperparameters were found using the grid search technique.

Cross-validation is a key method in machine learning for evaluating a model's generalization performance. Several subsets, sometimes called folds, are created from the provided data. These folds should ideally represent the

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distribution of the complete dataset. The original dataset is divided into three sets: 1656 images for the test set, 826 images for the validation set, and 5778 images for the training set, with a ratio of 7:1:2. A more reliable measure of the model's capacity for generalization is obtained by averaging the evaluation outcomes (such as accuracy, precision, and recall) from each iteration. Overfitting is lessened via cross-validation. K-fold cross-validation is a flexible and popular method for evaluating the generalizability of a model. Ten is the K-value that is set. It provides a solid method for measuring how successfully the GAN-pseudo labeling system detects knee OA.

In this work, we chose the image size of 224 × 224 pixels that yielded the greatest KL grade classification performance for ResNet-101, DenseNet-161, VGG16 and VGG19, four deep learning-based classification models. The Pytorch framework is used throughout the development of the code, and a 12GB Tesla K40c GPU has been used for every experiment. For the KL grade classification challenge, we choose the best model for each deep learning architecture based on performance criteria such as F1-score, precision, recall and classification accuracy (Accuracy). The objective is to discriminate between healthy knee joints and those affected by osteoarthritis based on medical imaging data; accuracy is a frequently used performance parameter for knee osteoarthritis diagnosis. Accuracy as in (4) gives a complete assessment of the model's rightness by counting the percentage of appropriately classified cases from all the instances in the dataset.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100\% \quad (4)$$

The number of correct predictions is the number of knee joints accurately identified as osteoarthritic or healthy. The total number of predictions is the dataset's overall number of knee joints.

Another critical performance indicator for knee osteoarthritis detection is precision as in (5), which is the ability to discriminate between knee joints in good condition and those impacted by the disease. Of all the model's positive predictions, precision indicates the percentage of accurate positive predictions. The following formula is used to determine precision when it comes to knee osteoarthritis detection:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (5)$$

The number of knee joints accurately diagnosed as osteoarthritic is called True Positives (TP). The number of knee joints mistakenly diagnosed as having osteoarthritis (predicted as having osteoarthritis but healthy) is known as False Positives (FP).

One crucial performance indicator for identifying knee osteoarthritis is recall as in (6). It computes the percentage of true positive predictions or correctly diagnosed cases of osteoarthritis. Recall is determined from the perspective of knee osteoarthritis recognition using the following formula:

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (6)$$

The number of knee joints accurately diagnosed as osteoarthritic is called True Positives (TP). The number of knee joints misclassified as healthy (i.e., anticipated as healthy but having osteoarthritis) is known as False Negatives (FN).

A popular performance statistic for knee osteoarthritis identification that strikes a compromise between recall and precision is the F1 score. It is particularly useful when there is an inequity between the classes (for example, healthier knee joints than osteoarthritic knee joints) and where it is crucial to consider both false positives and false negatives. The harmonic mean of precision and recall is used to compute the F1 score in the perspective of knee osteoarthritis recognition as in (7).

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (7)$$

Precision represents the proportion of true positive predictions among all positive predictions made by the model. Recall, on the other hand, denotes the percentage of true positive predictions among all actual positive cases of osteoarthritis within the dataset. Table 2. Shows the evaluation values of all the models

Table 2. Evaluation Results

Model / Metrics	ResNet-101	DenseNet-161	VGG16	VGG19
Training Accuracy	0.9623	0.7846	0.8956	0.7274
Training Loss	0.1368	0.4737	0.3576	0.3492
Testing Accuracy	0.9248	0.6942	0.7035	0.7024
Testing Loss	0.1758	0.3458	0.4357	0.3596
Precision	0.963	0.7136	0.7383	0.7257
Recall	0.959	0.726	0.7395	0.7217
F1Score	0.9246	0.7036	0.7157	0.7168

Various models such as ResNet-101, DenseNet-151, VGG16, and VGG19 are Convolutional Neural Network (CNN) architectures for image classification tasks. The ResNet-101 has highest training accuracy of 0.9623, the highest testing accuracy of 0.9248, a low training loss of 0.1368 and a low testing loss of 0.1758. The ResNet-101 has high precision, recall and F1 score value.

The model loss in knee osteoarthritis detection is a measure of error between the actual labels applied to the training instances and the projected probability of osteoarthritis presence. Training machine learning models to correctly identify knee pictures as suggestive or non-indicative of osteoarthritis depends heavily on this loss function.

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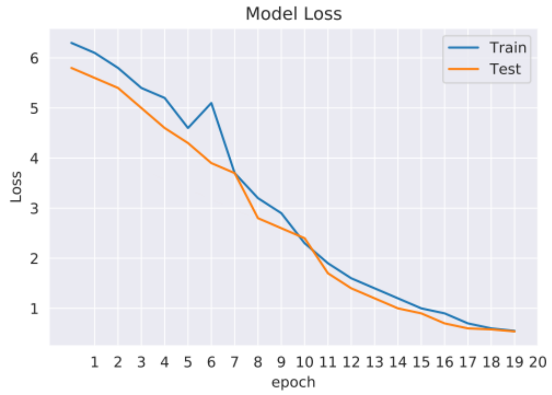

Fig. 5. Model loss at every epoch

Monitoring the model loss, one may evaluate how well training is going and steer the optimization process toward improved performance and generalization on untested data. Effective optimization of knee osteoarthritis detection models can be achieved by practitioners through experimentation with various loss functions and ongoing assessment of the model's performance metrics, including accuracy, precision, recall, and F1-score, for enhanced diagnostic accuracy and clinical value. Fig. 5 shows the model loss at every epoch. PyTorch and Keras, two deep learning frameworks, automatically record training and testing data. Metrics like accuracy for the training and test sets for each epoch are included in this timeline. With the help of Matplotlib, we can plot this data and produce a visual representation.

Model accuracy in knee osteoarthritis detection is the percentage of correctly categorized knee images relative to the total number of analyzed images. This measure is essential for evaluating how well machine learning models perform when taught to detect osteoarthritic changes in knee images precisely. Reaching a high level of model accuracy is essential to guaranteeing the validity of the diagnostic procedure and supporting medical practitioners in making well-informed decisions about patient care. The model's predictions are compared to the ground truth labels connected to the knee images to calculate the model's accuracy. The accuracy score is positively impacted by the model's ability to accurately identify osteoarthritis (positive cases) or the absence of osteoarthritis (negative cases). On the other hand, incorrect classifications lower the accuracy rating. Figure 5. Shows the model accuracy at every epoch.

The proposed work shows how sophisticated machine learning methods, such as pseudo-labeling and generative adversarial networks (GANs), can improve the robustness and accuracy of osteoarthritis identification from medical imaging data. The proposed models achieve good accuracy and performance across many datasets, demonstrating better generalization capabilities by utilizing semi-supervised learning with pseudo-labeling and GAN-generated false images. Additionally, the performance of the various models, such as ResNet-101, DenseNet-161, VGG16 and VGG19, is highlighted by the proposed comparative analysis of CNN architectures, where ResNet shows the highest accuracy, precision, recall, and F1-score.

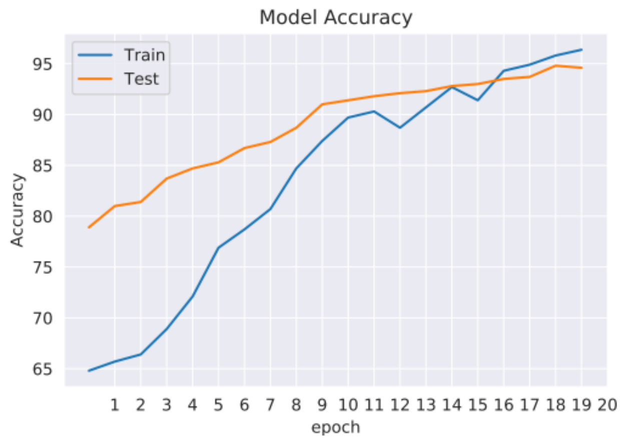

Fig. 6. Model Accuracy at every epoch

These results highlight the importance of choosing model architectures suitable for identifying osteoarthritis. Despite the encouraging results, we endorse the limitations of the investigation, notably the reliance on specific datasets and the need for additional validation on bigger and more diverse cohorts. Future research should look into other data augmentation techniques, modify model hyperparameters, and assess the methodology in actual clinical settings to aid in its application in clinical settings. The research advances the medical image analysis field and can potentially enhance patient outcomes in the treatment of osteoarthritis. Table 3 shows the comparative analysis of the existing approaches with the proposed approach.

Table 3. Comparative analysis between existing techniques and the proposed method

Author	Year	Precision	Recall	F1 Score
Ming Ni [21]	2021	0.5	NA	0.667
Dilovan Asaad Zebari [22]	2022	0.878	0.9	NA
Sameh Abd El-Ghany [23]	2023	0.8757	0.9129	0.8927
Proposed Method	2024	0.963	0.959	0.9246

V. CONCLUSION

The proposed work introduced a unique method for knee osteoarthritis detection that uses ResNet, DenseNet, VGG16, and VGG19 convolutional neural network (CNN) architectures for classification after generative adversarial networks (GANs) are used for data augmentation and pseudo-labeling. We have shown via thorough experiments that this method works well to increase robustness and accuracy in the detection of osteoarthritis. The proposed models have benefited from labeled and unlabeled data by using GANs to create fake images and adding pseudo-labeling, improving generalization skills. Additionally, we compared the performance of other CNN designs and found that ResNet performed the best in accuracy and F1 score. The results highlighted how cutting-edge machine learning methods might improve osteoarthritis diagnosis effectiveness and clinical applicability.

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