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DEEP LEARNING-BASED CLASSIFICATION OF KNEE OSTEOARTHRITIS USING GAUSSIAN NOISE AUGMENTATION AND KNOWLEDGE DISTILLATION

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ABSTRACT

Knee osteoarthritis (KOA) is a degenerative joint disease characterized by cartilage deterioration, leading to pain, stiffness, and impaired joint function. Accurate detection and grading are crucial for early intervention, but challenges such as limited data, redundant features, and suboptimal classification performance hinder reliable diagnostic tools. This study pro- poses an effective pipeline for classifying KOA into Kellgren- Lawrence (KL) grades 0 (no OA) and 2 (moderate OA) using data augmentation, deep feature extraction, and refined feature selection. The method was tested on 688 knee radiographs from the Osteoarthritis Initiative (OAI), with regions of interest (ROIs) extracted and augmented using Gaussian noise. Deep features were obtained via DenseNet-201, followed by knowledge distillation for feature selection, and classification was performed using a fine Gaussian Support Vector Machine (GSVM) with 5-fold cross-validation. The pipeline achieved 94.5% accuracy and a 96% AUC, whereas omitting feature selection reduced accuracy to 82%, and excluding augmentation lowered it to 88%, underscoring their importance. The integration of Gaussian noise augmentation, DenseNet-201, and knowledge distillation significantly enhanced classification performance, demonstrating strong potential for improving automated diagnostic systems and supporting early KOA detection and clinical decision-making.

Keywords: knee OsteoArthritis; X-ray images; Knowledge distillation; DenseNet-201; GSVM.

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1. INTRODUCTION

Knee Osteoarthritis (KOA) is a prevalent degenerative joint disease characterized by the gradual deterioration of articular cartilage, leading to pain, stiffness, and reduced mobility, It is the most common form of arthritis, affecting millions of individuals worldwide, particularly those over the age of 50 [1]. Epidemiological studies indicate that the incidence of KOA is increasing, influenced by factors such as aging populations, obesity, and joint injuries [2]. Radiographic imaging plays a crucial role in the diagnosis and evaluation of KOA, This imaging modality is essential for assessing structural changes in the knee joint, such as cartilage loss, bone marrow lesions, osteophyte formation, and joint space narrowing. The severity of KOA is typi- cally classified using grading systems such as the Kellgren- Lawrence (KL) scale [3], which categorizes the disease into stages ranging from 0 (no radiographic features of OA) to 4 (severe OA with extensive joint damage). Accurate staging is vital for determining appropriate treatment strategies and monitoring disease progression. However, manual assessment of OA severity through imaging is often subjective and time consuming, leading to variability in diagnosis and staging. To address these challenges, there is a growing necessity for the development and implementation of automatic detection and classification methods through advanced image processing techniques. Deep learning [4] has emerged as a transformative approach in medical imaging, offering enhanced accuracy and efficiency in disease detection and classification. By leveraging large datasets and advanced neural networks, deep learning models can identify subtle patterns and features in medical images that are often imperceptible to the human eye. This capability is particularly beneficial for KOA diagnosis, where early detection and precise classification are paramount for effective treatment and improved patient outcomes.Several recent studies have explored automated classifica- tion approaches for knee osteoarthritis (OA) diagnosis using various feature extraction techniques and classifiers. Janvier et al. [5] employed fractal analysis coupled with logistic regression, achieving an accuracy of 73% . In 2018, Riad et al. [6] applied the Dual-Tree Complex Wavelet Transform (DTCWT) with an SVM-RBF classifier, reporting a higher accuracy of 80.38%. Brahim et al. [7] utilized Power Spec- tral Density (PSD) features alongside logistic regression and obtained an accuracy of 78.92%. More recently, Ribas et al. [8] implemented a convolutional neural network (CNN)- based approach, achieving an accuracy of 81.69% on the same dataset. These methods demonstrate the evolution from traditional texture-based techniques to deep learning models, with CNNs showing promising improvements in classification performance.

In this study, we propose a novel machine learning-based approach for the detection of knee OA that includes several innovative techniques, including data augmentation with Gaussian noise method, feature extraction with DenseNet-201 model, feature selection with knowledge

distillation, and classification with Gaussian Support Vector Machine (GSVM),The proposed approach aims to improve the accuracy and interpretability of knee OA detection, making it more suitable for clinical use.

2. MATERIALS AND METHODS

2.1. Dataset

The dataset used in our experiment was obtained from the publicly accessible OAI [9]. The dataset comprises 688 radiographs of the knee, specifically focusing on the medial ROI of the tibia. These radiographs have been categorized using the Kellgren and Lawrence rating system (KL0, KL2). We compared grade (no OA) to disease overall grade KL2 (mild OA).Figure below shows the ROI used in our work.

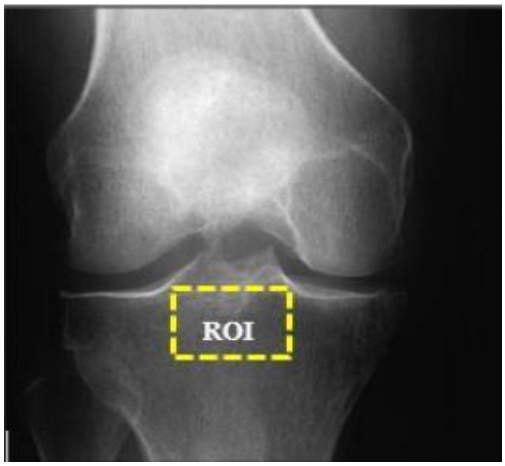


Fig.1. ROI used.

2.2. Methods

This section outlines the workflow of our framework for KOA classification, as illustrated in Figure2 . The pipeline be- gins with Gaussian noise-based augmentation to mitigate class imbalance in the dataset of 688 knee radiographs (evenly split between KL grades 0 and 2) from the OAI dataset. Following preprocessing and ROI extraction to focus on anatomically relevant regions, the method employs DenseNet-201 for deep feature extraction, leveraging its dense connectivity pattern for comprehensive feature representation. These features are then refined via knowledge distillation (KD) to prioritize the most discriminative characteristics while reducing redundancy. Finally, the optimized feature set is classified using a fine Gaussian Support Vector Machine (GSVM), selected for its effectiveness with high-dimensional medical data.

2.2.1. Data Augmentation

A major challenge in KOA detec- tion is the limited availability of annotated medical imaging data, which can restrict the performance of diagnostic models. To address this limitation while ensuring the preservation of critical pathological features, we employ Gaussian noise-based data augmentation. This

technique enhances dataset diversity by introducing controlled variations that mimic real-world imaging noise characteristics while maintaining the structural integrity of radiographic findings [10].

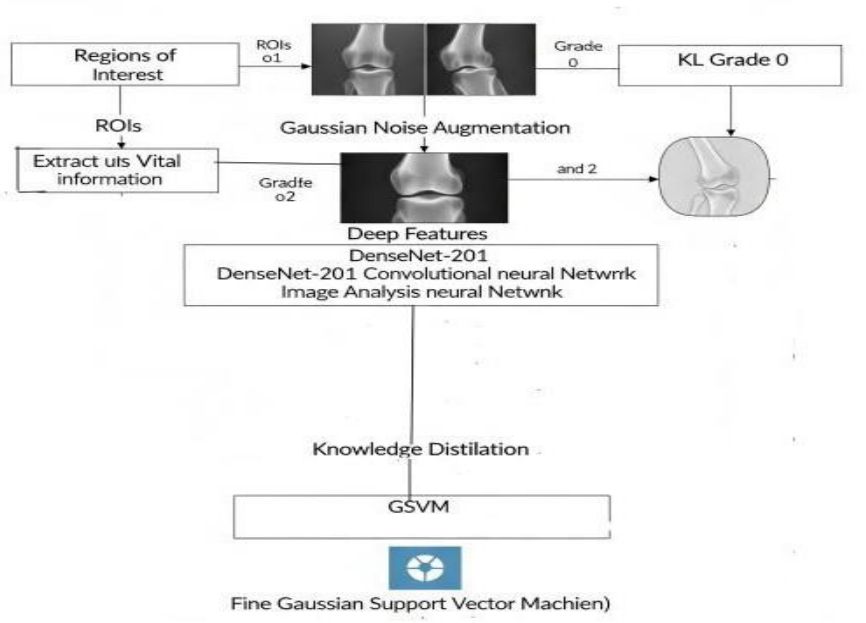


Fig.2. The proposed methods

The application of GNDA involves the addition of Gaussian noise to the original dataset. This noise is mathematically modelled as a Gaussian distribution with a mean (μ) of zero and a given variance (σ^2), essential for maintaining the integrity of the original data's distribution while introducing variability.

The GNDA can be represented by the following equation:

$$X' = X + \varepsilon \tag{1}$$

Where:

- X represents the original data sample.
- ϵ denotes the Gaussian noise, a random variable drawn from $N(0, \sigma^2)$.
- X' is the resultant augmented data point.

The Gaussian distribution, defined by the probability density function (PDF), is given as:

$$f(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{2}$$

2.2.2. Features extraction

DenseNet201 [11] is a convolutional neural network known for its dense connectivity, where each layer receives inputs from all previous layers, enhancing feature reuse and gradient flow. It

has 201 layers organized into dense blocks and transition layers, enabling efficient and rich feature extraction from images. Typically, input images are resized to 224×224 pixels, and the model outputs high- dimensional feature maps , which can be used for various classification tasks. DenseNet201's architecture reduces the vanishing gradient problem and improves learning efficiency, making it effective for extracting detailed and discriminative features in applications like medical image analysis and object recognition.

2.2.3. Features Selection

Features -based KD involves transferring internal representations from a teacher model to a student model [12], allowing the student to learn the intricate structures and relationships embedded in the teacher's feature maps (Figure 3). This method offers a more comprehensive knowledge transfer compared to merely replicating output probabilities.

Fig.4. The generic teacher-student framework for KD.

The loss function in feature-based KD is designed to align the intermediate feature representations of the teacher and student networks, typically formulated as:

$$L_{feature} = \frac{1}{N}\sum_{i=1}^{N} \| F_T^t - F_s^t \| \frac{2}{2} \quad (3)$$

Where:

- L_{feature} represents the feature-based KD loss.
- N denotes the number of feature layers or map points included in the distillation process.
- $\| \ \|^2$ indicates the squared Euclidean (L_2) norm, mea- suring the difference between the teacher's and student's feature maps.

The total KD loss combines the feature-based distillation loss with the task loss (typically cross-entropy loss), and is expressed as:

$$L_{KD} = \alpha L_{CE} + (1 - \alpha) L_{feature} \quad (4)$$

Here, α is a hyperparameter that determines the weighting between the feature-based distillation loss and the cross- entropy task loss.

2.2.4. Classification

After the feature selection process, where the most informative DenseNet features were identified through knowledge distillation (KD), a Gaussian SVM clas- sifier was employed for the binary classification of KOA into KL grades 1 and 2. The Gaussian SVM , utilizing a radial basis function (RBF) kernel, was chosen for its ability to model complex nonlinear decision boundaries in the high-dimensional feature space derived from DenseNet. This approach enabled the classifier to effectively discriminate between subtle structural and textural variations in knee joint regions, as encoded by the distilled feature representations.

3. RESULTS AND DISUSION

The bar chart in figure 4presents a performance comparison of different data augmentation strategies used in conjunction with a Densenet201-based model, measured by classification accuracy. Three configurations are shown: without GNDA (Gaussian Noise Data Augmentation), without KD (Knowledge Distillation Data Augmentation), and the full model combining GNDA + Densenet201 + KD. When GNDA is excluded, the accuracy drops to 82.6%, indicating that Gaus- sian noise augmentation significantly contributes to improving model generalization and robustness. When Knowledge Dis- tillation is removed, accuracy is 88%, suggesting that it also provides valuable performance gains, though slightly less than GNDA in this context. The best performance is achieved by the full combination GNDA + Densenet201 + KD with an accuracy of 94.5%, demonstrating that the integration of both augmentation techniques leads to the most effective learning and model performance.

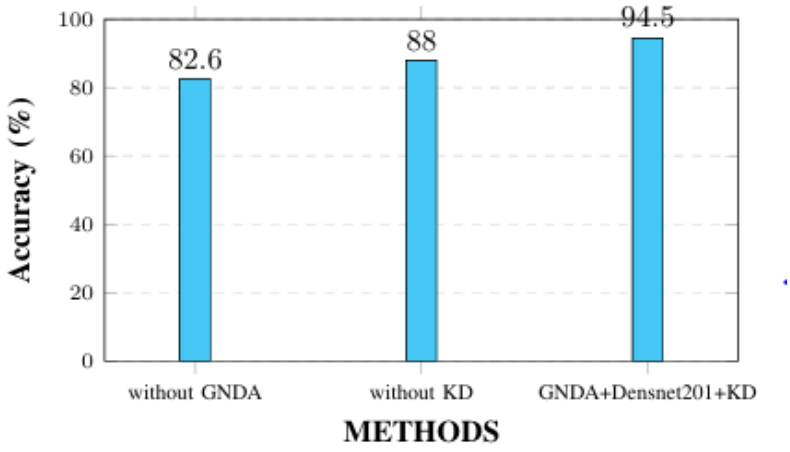


Fig.4. Performance comparison of different methods.

The figure5 displays the Receiver Operating Characteristic (ROC) curve, a common tool for evaluating the performance of a binary classifier. The true positive rate (sensitivity) is plotted against the false positive rate at various threshold settings. The blue curve represents the ROC, and the light blue shaded area under it corresponds to the Area Under the Curve (AUC), which in this case is 0.99. An AUC of 0.99 indicates excellent classifier performance, suggesting that the model has a very high ability to distinguish between the two classes. Additionally, a highlighted point on the curve at coordinates (0.07, 0.96) represents the current operating point of the classifier meaning it achieves a true positive rate of 96% with only a 7% false positive rate. This balance between sensitivity and specificity demonstrates that the model is highly effective and reliable for the classification task.

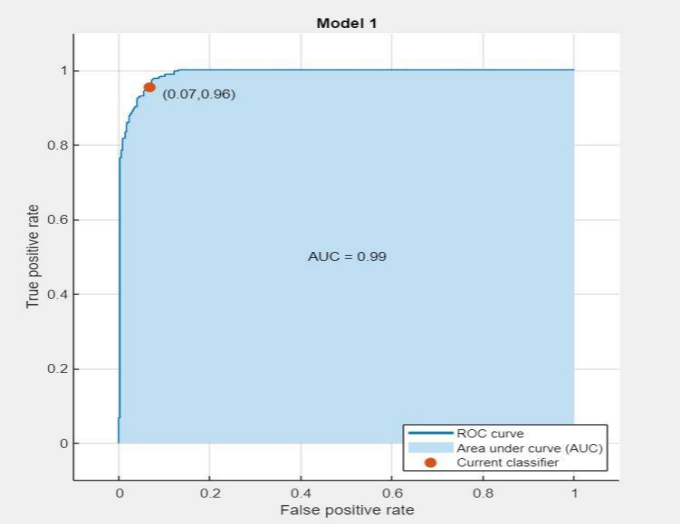


Fig.5. The ROC curve.

Table 1 summarizes the performance of various classification methods on a dataset of 688 samples. Traditional approaches like fractal analysis with logistic regression [5] achieved limited accuracy (AUC 0.73). Improvements were seen with DTCWT + SVM-RBF [6] and PSD + logistic regression [7], reaching accuracies of 0.8038 and 0.7892, respectively. Ribas et al. [8] later introduced a CNN model with a slight performance gain (accuracy 0.8169). The proposed method combining GNDA, DenseNet201, knowledge distillation, and Gaussian SVM outperforms all previous approaches with a 0.99 accuracy, demonstrating the power of deep learning and optimized classification.

Table 1. Comomparison of methods with the proposed approach.

Authors	**Year**	**Methods**	**Classifier**	**Data**	**Acc**
Janvier et al. [5]	2017	Fractal analysis	LR	688	0.73
Riad et al.[6]	2018	DTCWT	SVM-RBF	688	0.8038
Brahim et al [7]	2019	PSD	LR	688	0.7892
Ribas et al. [8]	2023	CNN	-	688	0.8169
Proposed methods	**2025**	**GNDA+DensNet201**	**GSVM**	**688**	**0.945**

4. CONCLUSION

This study presented an effective KOA classification pipeline combining data augmentation, DenseNet-201 feature extraction, and knowledge distillation-based feature selection, achieving 94.5% accuracy in distinguishing KL grades 0 and 2. The results highlight the importance of feature selection and augmentation, as their exclusion significantly reduced performance. The method shows promise for improving auto- mated KOA diagnosis, supporting early detection and clinical decision-making. Future work could expand to multi-class grading and larger datasets for broader validation.

5. ACKNOWLEDGEMENTS

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