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A Survey on KOA-CCTNet: Optimized Compact Convolutional Transformer for Osteoarthritis Severity Detection

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Abstract: Knee osteoarthritis(OA) is a prevalent degenerative a condition affecting the joints that significantly impacts the quality of life. Early and accurate diagnosis is critical for effective management and treatment. This project, titled "Automated Knee Osteoarthritis Prediction and Classification utilizes Xray imaging along with deep learning methods to propose an innovative method for diagnosing and grading knee(OA) by applying deep learning models. The system is developed using Python for backend computation, Flask as the web framework, and HTML, CSS, and JavaScript for the front-end. Two stateof-the-art advanced AI models, VGG16 and MobileNetV2, have been employed to classify X-ray images of knee joints into five categories on the Kellgren and Lawrence grading system: Normal, Doubtful, Mild, Moderate, and Severe. The dataset consists of 8bit grayscale X-ray images obtained through recognized hospitals and diagnostic centers using the PROTEC PRS 500E X-ray machine. Each image has been reviewed and labeled manually by two medical experts for accuracy and reliability. The VGG16 and MobileNetV2 models have been thoroughly evaluated. We measured performance using well-established metrics, namely accuracy, precision, and recall and F1-score,Confusion Matrix, have been computed to assess each model comprehensively. The findings of this study highlight the capability through the use of deep learning to facilitate automated KOA detection and grading.

I. INTRODUCTION

Knee osteoarthritis (OA) is considered to be a major prevalent musculoskeletal disorders worldwide, particularly affecting older adults and individuals who may be at higher risk because of factors like obesity or prior joint injury. The disease is defined by the gradual deterioration of articular cartilage, which results in pain, stiffness, swelling, and reduced mobility, ultimately diminishing patients' quality of life. With the combined effects of rising obesity rates and an aging global population, the incidence of knee OA continues to increase, making it a pressing public health challenge.

Diagnosis and severity assessment are most commonly performed through radiographic imaging and clinical evaluation, with the Kellgren–Lawrence (KL) grading system serving as the established standard. This system classifies radiographs into five stages ranging from ranging from normal to severe. While effective as a diagnostic tool, the manual grading process is often subjective, time-intensive, and vulnerable to inter-observer variability, especially when clinicians have differing levels of experience. These limitations underscore the need for more reliable, efficient, and objective diagnostic methods that can support clinical decision-making.

In recent years, advances in artificial intelligence (AI), particularly deep learning, have shown tremendous potential for transforming medical image analysis. Convolutional neural networks (CNNs) have excelled at learning localized features from imaging data, while Transformer models have done a great job at capturing broader contextual patterns. However, many existing approaches face challenges in balancing these complementary strengths, and their effectiveness can be decreases when handling complex or ambiguous cases of OA.

To address these gaps, we propose an improved deep learning framework designed specifically for automated knee OA grading from radiographic images. The framework integrates a modified compact convolutional transformer (CCT) with improved feature extraction strategies, enabling it to effectively capture both spatial detail and global context. By combining the advantages of CNNs and transformers, the proposed system seeks to improve diagnostic consistency and accuracy compared to conventional approaches. Its performance is rigorously validated using key measures including accuracy, precision, recall, F1-score, and confusion matrices, ensuring both clinical reliability and practical relevance for real-world healthcare applications.

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II. BACKGROUND AND MOTIVATION

A. *Characteristics of Knee Osteoarthritis (KOA)*

- Progressive Degeneration: KOA is marked by gradual cartilage deterioration, bone friction, and the formation of osteophytes.
- Symptom Variability: Patients experience pain, stiffness, and reduced mobility, but clinical signs don't always match with radiographic severity.
- Radiographic Assessment: X-ray imaging, particularly the Kellgren–Lawrence (KL) grading system, remains The standard approach for evaluating disease progression.

B. *Challenges in Automated KOA Assessment*

- Subjectivity in manual grading due to inter-observer variability.
- Limited and imbalanced medical datasets affecting model training.
- Inability of CNNs to detect long-range dependencies; transformers being data-hungry and computationally expensive.

C. *Motivation for Enhanced Deep Learning Models*

Traditional CNNs miss long-range dependencies, while transformers demand vast datasets and high computation. KOA radiographs are heterogeneous, requiring robust augmentation, advanced pre-processing, and hybrid models like CCT that integrate local and global features for accurate and clinically relevant grading.

III. LITERATURE SURVEY

A. *"Global,regionalprevalence,incidence and risk factors of knee osteoarthritis in population-based studies, "*

METHODOLOGY:A detailed review of studies, along with a meta-analysis drew upon PUBMED, EMBASE, and SCOPUS databases, emphasizing population-based observational studies to estimate the global prevalence and incidence of knee osteoarthritis.Data from 88 studies were synthesized using random-effects meta-analysis and subgroup analysis. LIMITATIONS:High heterogeneity across studies, exclusion of hospital-based studies, and no gray literature search limit generalizability. Early symptomatic and radiologically confirmed OA could not be separated.

B. *"A health-impact assessment of an ergonomic measure toreduce the risk of work-related lower back pain, lumbosacral radicular syndrome and knee osteoarthritis among floor layers in The Netherlands"*

METHODOLOGY:The study applied a health-impact assessment using Population Attributable Fraction (PAF) and Potential Impact Fraction (PIF) to estimate health gains from manually movable screed-levelling machines, based on observations of 28 floor layers.

LIMITATIONS:Small sample size, observational bias, and reliance on literature estimates limit accuracy, while results generalize only to Dutch floor layers.

C. *"Automating classification of osteoarthritis according tokellgrenlawrence in the knee using deep learning in an unfiltered adult population"*

METHODOLOGY:A ResNet CNN was trained on 6103 radiographic knee exams categorized by the Kellgren & Lawrence scale, with performance validated against expert consensus. The dataset was separated into three parts—training, validation, and testing. Image quality control excluded poor images and pediatric cases to enhance dataset consistency.

LIMITATIONS:Test set biased towards OA cases and excluded pediatric data, limiting generalizability. No external dataset validation, and potential overfitting despite cross-validation. Lack of investigation into model performance on early OA detection reduces clinical usefulness.

D. *"BreastNet18: A high accuracy fine-tuned VGG16 modelevaluated using ablation study for diagnosing breast cancer from enhanced mammography images."*

METHODOLOGY:Developed BreastNet18 based on finetuned VGG16, using preprocessing, data augmentation, and ablation study to classify mammograms into cancer types, with performance evaluated by accuracy and k-fold crossvalidation.

LIMITATIONS:Limited original dataset, potential overfitting, and reliance on augmented data without external validation. Model interpretability for clinicians was not assessed.

E. "A robust framework combining image processing anddeep learning hybrid model to classify cardiovascular diseases using a limited number of paper-based complex ECG images."

METHODOLOGY:Proposed InRes-106 hybrid CNN model combining InceptionV3 and ResNet50, enhanced by image preprocessing and ablation studies, to classify paper-based ECG images across five disease categories.

LIMITATIONS:Small, imbalanced dataset with variable image quality; no data augmentation applied, and no testing on digital ECGs limits applicability. Potential overfitting not fully ruled out.

F. "Deciphering knee osteoarthritis diagnostic features withexplainable artificial intelligence: A systematic review,"

METHODOLOGY:This paper systematically reviews explainable artificial intelligence (XAI) approaches applied to knee osteoarthritis (OA) diagnosis. It evaluates interpretability techniques, including data- and model-level methods, and compares existing datasets, classification systems, and clinical implications

LIMITATIONS:The review notes that many AI models for OA remain "black-box" and lack domain-specific adaptations. Existing XAI frameworks may not fully integrate clinical needs, and scalability in real-world practice is still uncertain.

G. "Vision transformers are robust learners."

METHODOLOGY:This work investigates the robustness of Vision Transformers (ViTs) through six systematically designed experiments. It benchmarks ViTs against CNN-based Big Transfer (BiT) models using six ImageNet datasets, analyzing performance under corruption, perturbations, adversarial examples, and distribution shifts.

LIMITATIONS:ViTs require large-scale pretraining and strong regularization, which may not be feasible in limited-data settings. The study is restricted to ImageNet datasets and May not work the same for everyone in all real-world domains.

H. "Recognition of knee osteoarthritis (KOA) using YOLOv2and classification based on convolutional neural network,"

METHODOLOGY:The proposed method combines handcrafted (LBP) and deep features (AlexNet, DarkNet-53) reduced via PCA for KOA grade classification. Features are fused and classified with 10-fold cross-validation, while localization uses an ONNX-YOLOv2 detector trained with optimized hyperparameters.

LIMITATIONS:KOA detection suffers from poor contrast, noise, and varying knee gap positions, making accurate grading difficult. Despite improvements, the system depends on dataset size and quality, and its robustness in diverse clinical environments is untested.

I. "A novel COVID-19 detection model based on DCGAN anddeep transfer learning,"

METHODOLOGY:This paper integrates Deep Convolutional GAN (DCGAN) with CNNs to enhance image recognition by generating additional synthetic samples. Radar profile datasets with four categories are used, applying CNN for classification after GAN-based augmentation.

LIMITATIONS:GANs are prone to unstable training, underfitting, or overfitting due to parameter sensitivity. The work is dataset-specific (meteorological radar profiles), so its generalizability to broader domains remains limited.

J. "MNet-10: A robust shallow convolutional neural networkmodel performing ablation study on medical images assessing the effectiveness of applying optimal data augmentation technique,"

METHODOLOGY:MNet-10 is a shallow 10-layer CNN optimized through ablation studies and hyperparameter tuning. The model uses photometric and geometric augmentation techniques and is tested on eight medical datasets, achieving high accuracy across modalities.

LIMITATIONS:Deep CNNs usually require large datasets, but augmentation alone may not prevent overfitting. Model performance varies depending on augmentation choice, and resizing images can risk losing critical diagnostic information.

K. "High-precision multiclass classification for lung diseasediagnosis from chest X-rays with a modified MobileNetV2,"

METHODOLOGY:This study used the ChestX-ray14 dataset with 112,120 images for detecting 14 lung diseases. Preprocessing included CLAHE for contrast enhancement, Gaussian filtering for denoising, and data augmentation to address class imbalance. Multiple CNN models were tested, and MobileNetV2 showed the best performance. A fine-tuned version, MobileLungNetV2, was developed.

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LIMITATIONS:The dataset suffers from imbalance across disease classes, which may bias results despite augmentation. Labels Developed using NLP approaches of radiology reports can introduce inaccuracies. The method heavily relies on highquality annotated datasets, limiting applicability where such data is scarce.

L. "Melanoma image classification based on MobileNetV2network,"

METHODOLOGY:This research applied implementing transfer learning on MobileNetV2 for binary classification of melanoma into benign and malignant. The model utilizes a global average pooling layer in conjunction with two fully connected layers, forming the classification head.

LIMITATIONS:The reported accuracy (85%) indicates room for improvement compared to other deep learning approaches. Performance is constrained by dataset quality, imbalance, and size.

M. "X-ray cherenkov-luminescence tomography reconstruc-tion with a three-component deep learning algorithm: Swin transformer, convolutional neural network, and locality module,"

METHODOLOGY:The study proposed a system with three main parts(Swin transformer, CNN, and locality module) for reconstructing emission quantum yield in XCLT. The Swin transformer captured pixel-level priors from sinograms, CNN translated features to image space, and a locality module improved feature delivery. Validation was done using simulations, physical phantoms, and in vivo experiments, showing significant improvements in reconstruction metrics over filtered backprojection and AUTOMAP.

LIMITATIONS:The approach requires extensive the training data, which could place some limits feasibility in clinical practice. Although performance improved in experiments, realworld application faces challenges like noise, variability in biological tissues, and radiation dose constraints. Computational complexity of transformer models may hinder real-time processing. Clinical validation remains limited.

N. "CCTCOVID: COVID-19 detection from chest X-ray im-ages using compact convolutional transformers,"

METHODOLOGY:This study introduced Compact Convolutional Transformers (CCT) for automatic COVID-19 detection from chest X-rays. The model combined CNN-like convolutional layers with transformer-based architectures to identify both detailed and overall image features. Experiments on large datasets achieved a classification accuracy of 99.22%, outperforming existing CNN and ViT approaches.

LIMITATIONS:High accuracy may be dataset-specific, raising concerns about overfitting. Transformer-based models often require vast datasets and may generalize poorly with smaller samples. It does not fully test performance on large set of populations and imaging conditions. Practical deployment in low-resource clinical settings may face computational and interpretability challenges.

O. "An an approach that improves efficiency and reducescomputational cost by applying a modified CCT to lung disease detection classification, "

METHODOLOGY:This study used the COVID-19 Radiography dataset containing 21,149 X-ray images across four classes (COVID-19, Normal, Lung Opacity, and Viral Pneumonia).Data imbalance was managed with DCGAN to generate synthetic images, and preprocessing steps such as morphological opening, CLAHE, bilateral filtering, and gamma adjustment improved image quality.A MCCT was proposed with reduced layers, hyperparameter tuning, and studies for optimization. The model gained 95.37% accuracy.

LIMITATIONS:Although MCCT reduces the time, it relies heavily on synthetic data from GANs, which may not always replicate real-world variability. The evaluation was datasetspecific, raising concerns about generalization to unseen populations or imaging settings. The input resolution (32×32) may oversimplify image details critical in clinical diagnosis.

IV. METHODOLOGY

The KOA-CCTNet framework integrates data augmentation, advanced preprocessing, and CCT model to enhance knee osteoarthritis (KOA) grade assessment from X-ray images.

A. Dataset Preparation

Goal: Construct an extensive and varied dataset for robust KOA classification.

Technique: Data were aggregated from four sources, such as(Mendeley I Mendeley II, Kaggle,as well as the AIDA dataset) and removed low-quality/damaged images. Applied a regionof-interest isolation technique to focus on the cartilage area. Final dataset: 10,232 images.

Performance: Produced a balanced data hub across all KL grades (0–4), ensuring consistency and reliability in training.

B. Data Augmentation with DCGAN

Goal: Overcome class imbalance and expand dataset variability.

Technique: Employed DCGAN to generate synthetic X-ray images. Producer and classifier architectures were optimized with gradient descent to stabilize training.

Performance: Expanded dataset to 110,232 images (balanced across five KOA grades). Generated images were statistically validated (PSNR >31, SSIM >31) to confirm quality close to original X-rays.

C. Image Pre-processing

Goal: Enhance image clarity and standardize inputs for the model.

Techniques:In this study, several image pre-processing techniques were applicable to increase the overall quality of Xray images before being introduced into the model. Adaptive Histogram Equalization (AHE) was made to improve local contrast, allowing finer structural details within the knee joint to become more visible. To further refine image clarity, Fast Non-Local Means (FNLM) filtering was used, whichreduced noise effectively, The activity of these preprocessing steps was validated using quality metrics, achieving values ofMSE <0.33, PSNR >31, and SSIM >0.99,, which confirmed that diagnostic visibility was significantly enhanced while preserving critical information.

D. Transfer Learning Baselines

Goal: Benchmark KOA classification performance.

Technique: Tested five pretrained CNN models (VGG16, DenseNet201, InceptionV3, MobileNetV2, ResNet50) on the dataset.

Performance:Among the models tested, MobileNetV2 obtained one of the highest baseline accuracy(79.98%), but all gave weaker results than the proposed Transformer” model.

E. Transformer Models Evaluation

Goal: Identify the most efficient transformer-based backbone for KOA classification.

Technique: Compared four models—Vision Transformer
(ViT), Swin We worked with three models: Transformer, Involutional Neural Network,and CCT.

Performance: CCT achieved the best balance of accuracy (86.54%) and training speed, selected as the foundation for KOA-CCTNet.

F. Modified Compact Convolutional Transformer (KOACCTNet)

Goal: Improve classification accuracy while reducing training complexity. Technique:

- Reduced transformer encoder blocks from 2 → 1 for faster convergence.
- Adjusted stride = 1 and kernel size = 4.
- Optimized tokenizer output to 64×128 without positional encoding.
- Conducted nine ablation studies to fine-tune dropout, dense layers, batch size (128), optimizer (Adam, lr = 0.001).

Performance: Achieved 94.58% accuracy, with individual grade accuracies up to 99.29% (Grade 4). Outperformed CNN and transformer baselines in both accuracy and training efficiency.

G. Effectiveness of Components

- Data Augmentation (DCGAN): Improved classification accuracy from 80–88% (geometric/photometric methods) to 94.58%.
- Preprocessing (AHE + FNLM): Increased feature clarity and robustness against noise.
- Model Optimization: KOA-CCTNet outperformed Swin, ViT, and CNN models, showing higher robustness with reduced datasets (accuracy remained 87.55% with only 25% data).

V. CONCLUSION

The developed KOA-CCTNet framework demonstrated showed enhanced effectiveness in classifying KOA severity grades, achieving 94.58% accuracy and outperforming both CNN and transformer-based baselines. By integrating advanced augmentation, preprocessing, and a modified CCT architecture, the model ensured robustness even with reduced datasets.

These results highlight KOA-CCTNet as a reliable and efficient solution for automated KOA grade assessment using X-ray images.

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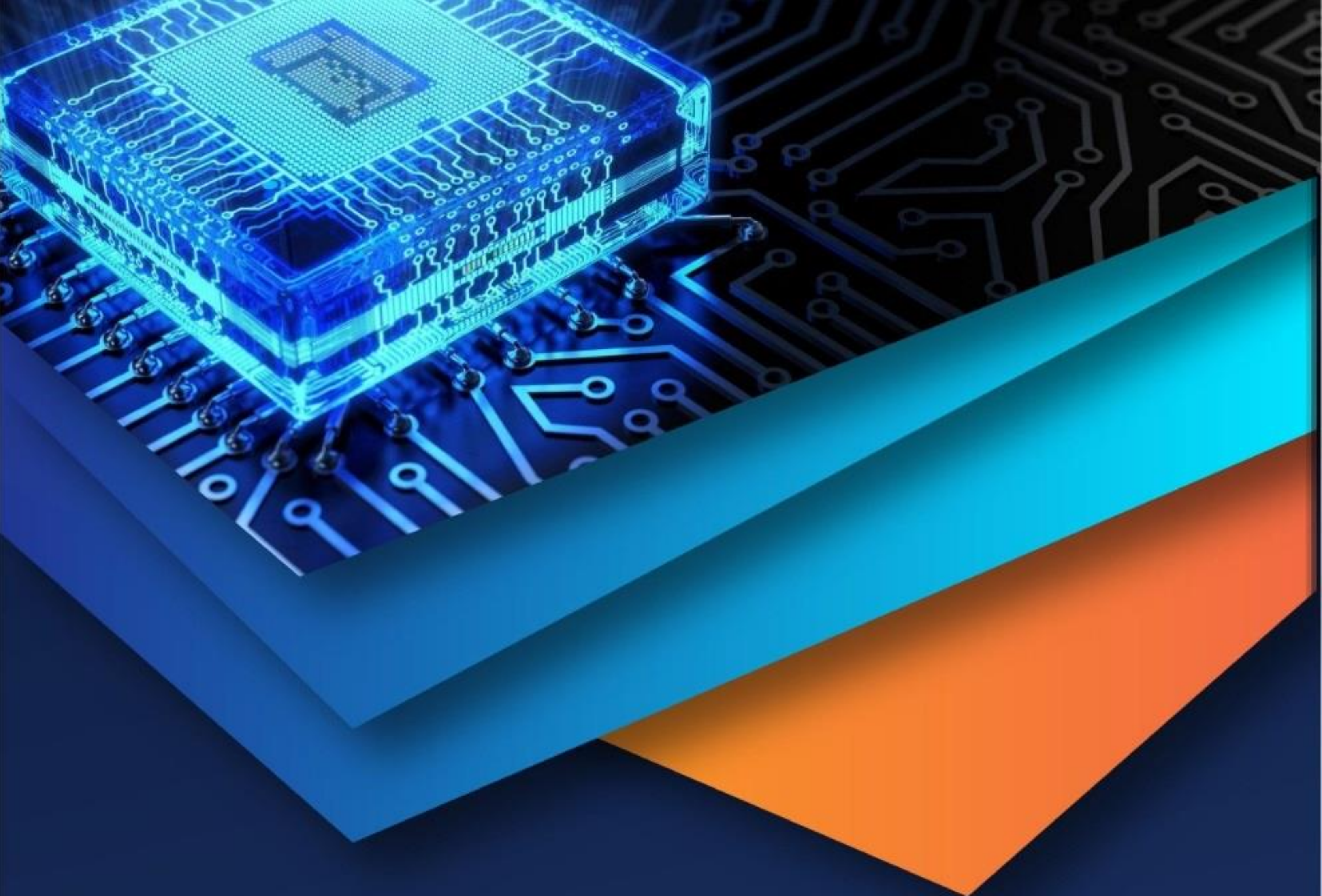

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