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A Sequential VGG16+CNN based Automated Approach with Adaptive Input for Efficient Detection of Knee Osteoarthritis Stages

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ABSTRACT Osteoarthritis (OA) stands as the most prevalent musculoskeletal disorder, particularly affecting the knee joint and causing substantial pain and functional impairment. Radiologists traditionally employ the Kellgren–Lawrence (KL) grading system, analyzing radiographic evidence from both sides of the knee bones, to evaluate OA severity. Knee X-Rays are considered a golden imaging modality to analyse the severity of Osteoarthritis. Many computer-aided methods aimed at enhancing diagnostic accuracy and efficiency, leveraging advancements in automated classification models utilizing Knee X-Rays. These innovations hold promise for improving the diagnosis and management of OA. In this paper, A new model (hybrid of CNN and VGG16) is proposed to utilize strength of both architectures to obtain accurate results for OA detection. Different neural networks (CNN, VGG16, VGG19, ResNet50, CNN-RestNet) are implemented and compared with the proposed method. Additionally, data augmentation contributes to enhanced accuracies across all models by resolving class imbalance problem. It is analysed that all models performed well on training set however, for testing set, the proposed hybrid method (CNN-ResNEt50) outperformed other state-of-the-art methods and produce accurate results for all five stages of OA using KL grading method. The proposed method obtained above 93% accuracy for training, validation and testing data.

INDEX TERMS Knee Osteoarthritis, X-Ray, Kellgren and Lawrence grading, VGG16/VGG19, ResNet50, Convolutional Neural Network (CNN)

I. INTRODUCTION

Osteoarthritis of the knee (KOA) was commonly associated with older individuals; however, it is now increasingly affecting people at younger ages [1] due to various risk factors, including but not limited to obesity, inadequate physical activity, trauma, genetic predisposition, gender and bone density [2], [3]. Knee arthritis stands as one of the prevalent conditions, emphasizing the crucial need for early intervention to prevent its advancement to more severe stages.

Knee osteoarthritis is characterized by the deterioration of the articular cartilage in the knee, which is the flexible and slippery material that typically shields bones from friction and impact within the joint [2]. A clear picture of a normal Knee X-Ray and Orthoarthritis X-Ray is shown in the Figure 1. This condition also brings about alterations in the bone beneath the cartilage and can impact adjacent soft tissues. Among arthritis types, knee osteoarthritis stands out as the predominant cause of knee pain and is commonly known as knee arthritis [4]. Although there are less prevalent forms of arthritis, such as rheumatoid arthritis, pseudogout, and reactive arthritis, that can also contribute to knee pain. This is imperative due to its substantial economic affect, potential for disability, significant pain, and significant impact on the patient's lifestyle [1], [2], [5]. Individuals affected by osteoarthritis (OA) commonly exhibit symptoms such as persistent pain, crepitus, swelling, morning stiffness, muscle atrophy, reduced quadriceps strength, and compromised postural control. These manifestations contribute to challenges in carrying out routine activities of daily living [6].

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FIGURE 1. Images of two knee X-Rays: With normal and loss of joint space

Medical experts determine the extent of knee osteoarthritis (OA) using the Kellgren and Lawrence (KL) grading method [7], designed for visual examination of X-ray images or MRI [8]. The KL system categorizes knee OA severity into five grades ranging from grade 0 (normal) to grade 4 (severe) [7], [9], these grades are outlined below and also shown in the Figure 2 :

- Grade 0: (Normal) Images of Healthy knee.
- Grade 1 (Doubtful): Images having uncertain joint narrowing a potential presence of Osteophytic Lipping.
- Grade 2 (Minimal): Images clearly depicting the presence of osteophytes along with potential joint space narrowing.
- Grade 3 (Moderate): Images showing the existence of numerous osteophytes, along with verified reduction in joint space and mild sclerosis.
- Grade 4 (Severe): Images displaying significantly large osteophytes, prominent joint narrowing, and intense sclerosis.

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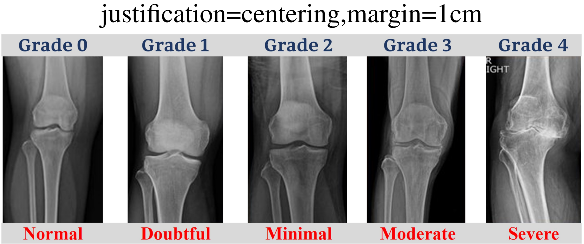

FIGURE 2. Different stages of OA in knee X-Rays: From Normal to Severe

Presently, osteoarthritis is diagnosed through physical examination and using some imaging modalities such as arthroscopy, X-ray, and MRI scans [2]. However, X-Ray (plain radiography) is considered as gold standard for diagnosing osteoarthritis (OA), in addition to the essential routine clinical examination of the symptomatic joint. This method is considered safe, cost-efficient, and widely accessible [10].

Several techniques have been used to address the early detection of OA. Invasive and non invasive methods like Shear wave elastography (SWE) [11], vibroarthrography (VAG) are used for OA. The growing utilization of ML-based techniques is helping professionals in the medical domain by either partially or fully automating the diagnostic process. Specifically, supervised ML-based approaches can assist medical practitioners in making more informed clinical decisions [12]–[14]. In the last decade many machine learning methods gave good results to automate the process of OA detection.Hybrid models, created by integrating VAG with machine learning methods, have been developed. Nevertheless, there is still ample room for improving these models or propose some new technique to improve accuracy and efficiency in detecting this critical disease to easy human life.

In this paper, a new approach is discussed which is based on Convolutional neural network CNN model and VGG16 architecture. This hybrid method utilizes the strengths of both models, allowing for a more comprehensive analysis of X-ray images. VGG16, known for its deep and intricate feature extraction capabilities [15], captures intricate patterns and subtle details present in knee X-Rays. Simultaneously, the CNN (Convolutional Neural Network) component enhances the model's ability to discern complex spatial relationships within the images [16], improving overall diagnostic accuracy. The hybrid model capitalizes on the complementary features of VGG16 and CNN, resulting in a more robust and effective system for knee OA diagnosis.

The primary contributions of this paper can be outlined as follows:

- A new model (hybrid of CNN and VGG16) is proposed to utilize strength of both architectures to obtain accurate results
- Different CNN models are implemented to analyse the results using same dataset
- Class imbalance problem present in the Osteoarthritis dataset is resolved using different techniques of data augmentation
- presented new state-of-the-art results in the diagnosis of knee OA using plain knee X-Rays

The structure of the paper is as follows: Section 2 provides an overview of the existing work done in the same area for the diagnosis of OA. Section 3 explains the proposed Computer-Aided Diagnosis (CAD) method. Section 4 presents the experimental results and subsequent discussion, while Section 4 outlines the conclusions drawn from the study.

II. LITERATURE REVIEW

Several methods have been used to detect knee osteoarthritis, some of them are fully automated and some are semi-automated. These methods utilize different imaging modal-

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ities, including Knee X-Rays and MRI scans [17] . In the context of knee osteoarthritis (OA), Shamir et al. [7] introduced a technique employing a sliding window strategy to pinpoint the knee joints. Antony et al. [18] proposed a fully convolutional network (FCN) system for knee joint detection and the automated quantification of KOA severity based on the KL scale. This approach demonstrated superior classification accuracy for KL grades 3 and 4 compared to grades 0, 1, and 2, attributed to subtle variations in the image(s).

In another study, Elastic Net (EN) and Random Forests (RF) was employed to construct predictive models utilizing patient assessment data, including signs and symptoms of both knees and medication use. Additionally, a convolutional neural network (CNN) was trained exclusively using X-ray images. They trained models to predict the severity levels of knee osteoarthritis (KOA) however, the subjectivity in the KL grade remains a primary concern.

A customized YOLOv2 model, due to it's success in multiple domains [19], was proposed for knee joint detection, coupled with the fine-tuning of convolutional neural network (CNN) models using a novel ordinal loss for knee KL grading [20]. This approach led to state-of-the-art performance in both knee joint detection and KL grading. They obtained 69.7 % accuracy using fine-tuned model.

Another research presents a computer-assisted diagnostic (CAD) system designed to detect and automatically classify knee osteoarthritis (OA) by processing X-ray images and assigning KL grades. The proposed model utilizes Deep Siamese convolutional neural networks and a fine-tuned ResNet34 architecture to concurrently detect issues in both knees [2]. Class imbalanced issue is resolved using transfer learning. The model achieved a multiclass accuracy of 61% for KL grading.

Different machine learning (ML) models were also employed to detect OA and knee KL grading. In a paper, different ML techniques were used [21]. Preprocessing was done using circular Fourier filter. Next, a novel normalization technique, relying on predictive modeling through multivariate linear regression (MLR), is employed on the data to minimize variability between subjects with osteoarthritis (OA) and those who are healthy. A publicly available X-Ray dataset OsteoArthritis Initiative (OAI) was used. ML methods show good classification rate for OA detection 82.98% for accuracy. The authors of [22] conducted a comprehensive review focusing on the application of machine learning (ML) techniques for diagnosing and predicting knee osteoarthritis (KOA). The survey, covering papers published from 2006 to 2019, categorized findings into segmentation, post-treatment planning, classification, and prediction/regression. Most diagnostic models exhibited accuracies ranging from 76.1% to 92%. The review emphasized the impact of ML in developing automated solutions for pre- and post-treatment in OA.

In [23], the authors introduce a discriminative regularized autoencoder for enhanced detection, aiming to capture both discriminative and meaningful features. By incorporating a discriminative loss in the training criteria, the model is encouraged to account for discriminative data. They used OAI database to conduct experiments, their method demonstrated an accuracy of 82.53%, surpassing other state-of-the-art deep learning techniques.

In another study, an ordinal regression module for neural networks specifically designed to treat KL grading as an ordinal regression task [24]. This module takes input from the neural network and generates four cut-points, strategically partitioning the prediction space into five distinct KL grades. Results show that they obtain maximum accuracy of 88.09% using DenseNet161.

Von et. al. proposed a model [25] to detect OA using a combination of intrinsic dimension reduction coupled with a graph convolutional neural network. OAI dataset was used for the research. They were able to obtain accuracy of 64.64%. In another research [26], the authors suggest an automated classification method for knee osteoarthritis images using deep neural networks (DNNs). After preprocessing the images, a two-step procedure is employed: initially, a VGG network is utilized to extract the knee joint center, followed by classification using the ResNet50 network. Results show good accuracy of 81.41%.

In [27], both traditional and deep models are used to enhance early knee osteoarthritis (KOA) detection performance. The traditional model incorporates random forest, neural networks, and logistic regression, while the deep neural networks employs convolutional neural networks (CNNs) for classifying knee images and predicting pain progression likelihood. Dataset of OAI is used to conduct research. A good accuracy of 81% is obtained and it is observed that combining traditional and deep learning learners (DLLs) on diverse datasets can yield improved KOA detection accuracy. Nevertheless, there is room for improvement in the performance of knee analysis. Given the ordinal nature of the KL grading task, enhancing the knee KL grading performance may be achieved through the adoption of a more effective loss function or some modified deep learning model.

III. PROPOSED METHODOLOGY

For diagnosing different stages of Knee Osteoarthritis, multiple algorithms are trained on bench mark dataset to achieve a robust diagnostic system.

A. DATASET

The dataset comprises 1650 digital X-ray images of knee joints gathered from renowned hospitals and reputable diagnostic centers [28]. These X-ray images are captured using the PROTEC PRS 500E X-ray machine and are in their original 8-bit gray scale format. Each radiographic knee X-ray image has been annotated and labeled according to Kellgren and Lawrence grading method by two medical experts. Detailed statistics of this dataset is given in the Table 1.

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B. DATA AUGMENTATION

Table 1 and 2 describe statistics of images used before and after applying data augmentation to resolve class imbalance problem. Different augmentation techniques (Horizontal flip, Vertical flip, Rotation -45, Rotation 90, Crop 0.1, Crop 0.2, Gaussian noise, Gamma contrast, Sigmoid contrast, Linear contrast, Channel shuffling, and Inverted colors) have been used to generate more images of Knee X-Rays to balance all five classes in the dataset. Figure 5 shows original knee X-Ray image and multiple X-Ray images generated using different augmentation techniques after applying on original image.

C. EXPERIMENTAL SETUP

For computer-aided diagnostic of Knee Osteoarthritis and it's severity level, a new model i.e., VGG-16+CNN is proposed and it's performance is compared with CNN, VGG-16, VGG-19 and ResNet50.

1) CNN

The CNN architecture, illustrated in Figure 3, is structured in a sequential manner, constructing the model layer by layer. Commencing with the input layer, its dimensions are determined by the input images. Subsequently, a 2D convolution layer with 32 filters and a kernel is added. The Rectified Linear Unit (ReLU) is employed for efficient computation and rapid convergence. To address the "vanishing gradient" issue, wherein ReLU yields zero for negative values, a LeakyReLU is introduced atop the convolution layer with an alpha value of 0.001. Following this, a dropout layer with dropout ratio 0.3 is incorporated.

After dropout layers, convolutional layer is again added accompanied by LeakyReLU and dropout layers with the previously defined parameters. Subsequent to these layers, an additional 2D convolution layer is introduced with the number of filters adjusted according to the size of input image. A pooling layer is then inserted to down-sample and summarize the feature map. To avoid over-fitting, a dropout layer follows the pooling layer in the network.

After this layer, a flattening technique is applied to the network's output, succeeded by two fully connected dense layers with 12 and 1 units, respectively. LeakyReLU and sigmoid functions serve as activation functions in these fully connected layers.

2) VGG-16

VGG16, is a well reputed variant of CNN which is constructed sequentially with layers that progressively build the model. Beginning with the input layer, the network features multiple 2D convolutional layers with 64 filters and a kernel, employing Rectified Linear Unit (ReLU) activation functions for computational efficiency. To address the "dying ReLU" issue, LeakyReLU is introduced with an alpha of 0.001, followed by dropout layers to prevent overfitting. This architecture includes additional convolutional layers, each utilizing specified kernel sizes, and concludes with fully connected dense layers having 4096 and 1000 units, with LeakyReLU and softmax as activation functions. The VGG16 design is characterized by its systematic layering and effectiveness in image classification tasks.

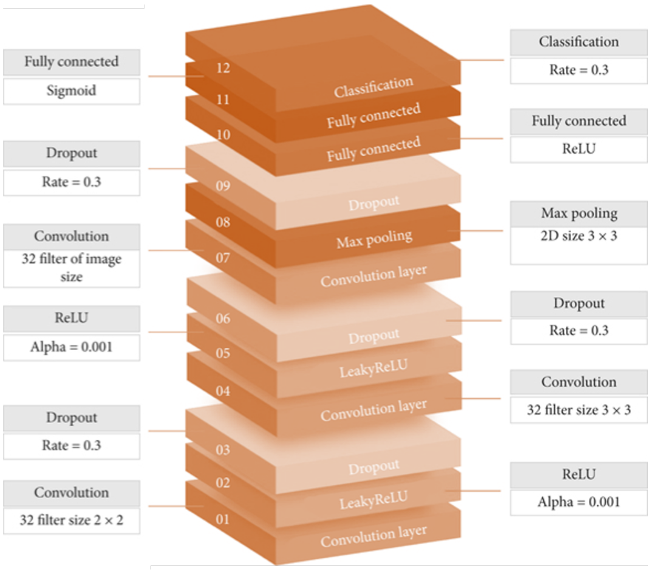

FIGURE 3. Architecture of Convolutional Neural Network (CNN) [29]

3) VGG-19

VGG19, another prominent CNN architecture, is systematically structured with sequential layers to construct the model. It initiates with the input layer, adapting its size to the input images. The architecture then incorporates a series of 2D convolutional layers, each featuring 64 filters and a kernel, utilizing Rectified Linear Unit (ReLU) activation functions for computational efficiency. To address the "dying ReLU" issue, LeakyReLU is added with an alpha value of 0.001, followed by dropout layers.. This sequential design includes additional convolutional layers, each employing specific kernel sizes. Towards the end of the architecture, fully connected dense layers are introduced, with units numbering 4096 and 1000, utilizing LeakyReLU and softmax activation functions, respectively. VGG19 follows a structured layering approach, incrementing the number of filters and units systematically, proving effective for image classification tasks.

4) ResNet50

ResNet50, a significant advancement in deep learning and CNN architectures, introduces a revolutionary concept of residual learning. To address the challenges of training networks with deep leayers, ResNet50 employs residual blocks, allowing the learning of residual functions instead of the entire mapping. Such a design makes it capable of the training of exceptionally deep layers in the networks thus making it less prone to vanishing or exploding gradient problems. The input layers is adaptable followed by multiple residual blocks, each containing convolutional layers with skip connections. The skip connections enable the direct flow of information, eliminating the degradation problem. ResNet50 contains fully connected layers for classification. The model incorporates 3.8 million trainable parameters, and 50 layers in total.

5) VGG-16+CNN

The proposed architecture, illustrated in Figure 4, comprises of two deep networks. The first deep network is VGG16 which extracts image features using sequential 2D convolutional layers with ReLU and LeakyReLU activations, addressing issues like the "dying ReLU" problem. The additional convolutional layers of VGG16 alongwith dropout mechanism contribute to effective feature extraction, culminating in fully connected dense layers. This systematic architecture makes VGG16 adept at capturing hierarchical features, which are crutial in image classification tasks. For classification, another convolutional deep learner is used which starts with an adaptive input layer and incorporates three 2D convolution layers with 32 filters and ReLU activation. LeakyReLU is used with alpha 0.001, followed by a dropout layer with rate 0.3. Additional layers include specified kernel sizes, LeakyReLU activations, and dropout mechanisms. The architecture concludes with a flattening step and two fully connected dense layers (12 and 1 units), using LeakyReLU and sigmoid activations, designed for efficient feature extraction and image classification.

TABLE 1. Statistics of original dataset: Total number of images for each class and its split into training,testing and validation sets

Class	Total	Train	Valid	Test
0	514	360	103	51
1	477	334	96	47
2	232	163	46	23
3	221	155	44	22
4	206	145	41	20
All	1650	1157	330	163

TABLE 2. Statistics of dataset after balancing classes: Number of images for training and testing and validation

Class	Total	Train	Valid	Test
0	6168	500	103	51
1	5724	500	96	47
2	2784	500	46	23
3	2652	500	44	22
4	2472	500	41	20
All	19800	2500	330	163

IV. RESULTS AND DISCUSSION

The dataset is partitioned into training, validation, and testing sets with a distribution of 70:20:10 (training:validation:testing) to conduct a thorough analysis of various models for osteoarthritis (OA) detection. Multiple neural network architectures, including CNN, VGG16, VGG19, and ResNet50, are employed. Results from these models are depicted in Table 3. Notably, no preprocessing or data augmentation is performed in obtaining these initial results. However, Is is observed that original data has skewness. To address this imbalance, different data augmentation techniques are employed.

The aforementioned models, along with a proposed model, are then applied to a newly balanced dataset, comprising the original dataset and augmented data. The outcomes of this application are presented in Table 4. It becomes evident that the proposed model surpasses other existing neural networks in performance. Additionally, data augmentation contributes to enhanced accuracies across all models.

the proposed model attains an accuracy of 93.27% in effectively detecting various grades of OA. These results are represented as the average accuracies for all five grades (described by KL method). The study underscores the significance of data augmentation in addressing class imbalance and emphasizes the superior performance of the proposed model in the context of OA detection.

TABLE 3. Training, Validation and Testing accuracy of CNN, VGG16, VGG19 and ResNet50

Model	Training	Validation	Test
CNN	99.27%	89.33%	88.3%
VGG16	92.22%	78%	79.98%
VGG19	87.28%	83.33%	84.14%
ResNet50	99.74%	75.15%	80.36%

TABLE 4. A performance comparison between CNN, VGG16, VGG19, ResNet50 and the proposed model (VGG16 + CNN), while considering Training, Validation and Testing accuracy

Model	Training	Validation	Test
CNN	99.71%	91.43%	90.38%
VGG16	94.32%	86.73%	88.45%
VGG19	91.89%	83.33%	84.14%
ResNet50	99.88%	87.88%	85.28%
Proposed Model	98.98%	95.52%	93.27%

Bar Charts are shown in figures 6 and 7 to show the performance of different models before and after applying data augmentation.

The proposed hybrid model, combines the VGG16 and CNN architectures, and shows superiority over individual models for knee osteoarthritis (OA) diagnosis using X-ray. It uses the complementary strengths of the two components. VGG16, known for its depth and hierarchical feature extraction capabilities, excels in capturing intricate patterns and abstract representations within the X-ray images. Its ability to learn complex hierarchical features is crucial in discerning important details which are used to indicate severity of OA disease. On the other hand, the CNN architecture likely contributes by efficiently extracting local features and patterns, helping in the recognition of specific abnormalities associated with OA. The integration of both models allows for a more comprehensive analysis, leveraging the strengths of each to create a more robust and accurate diagnostic method.

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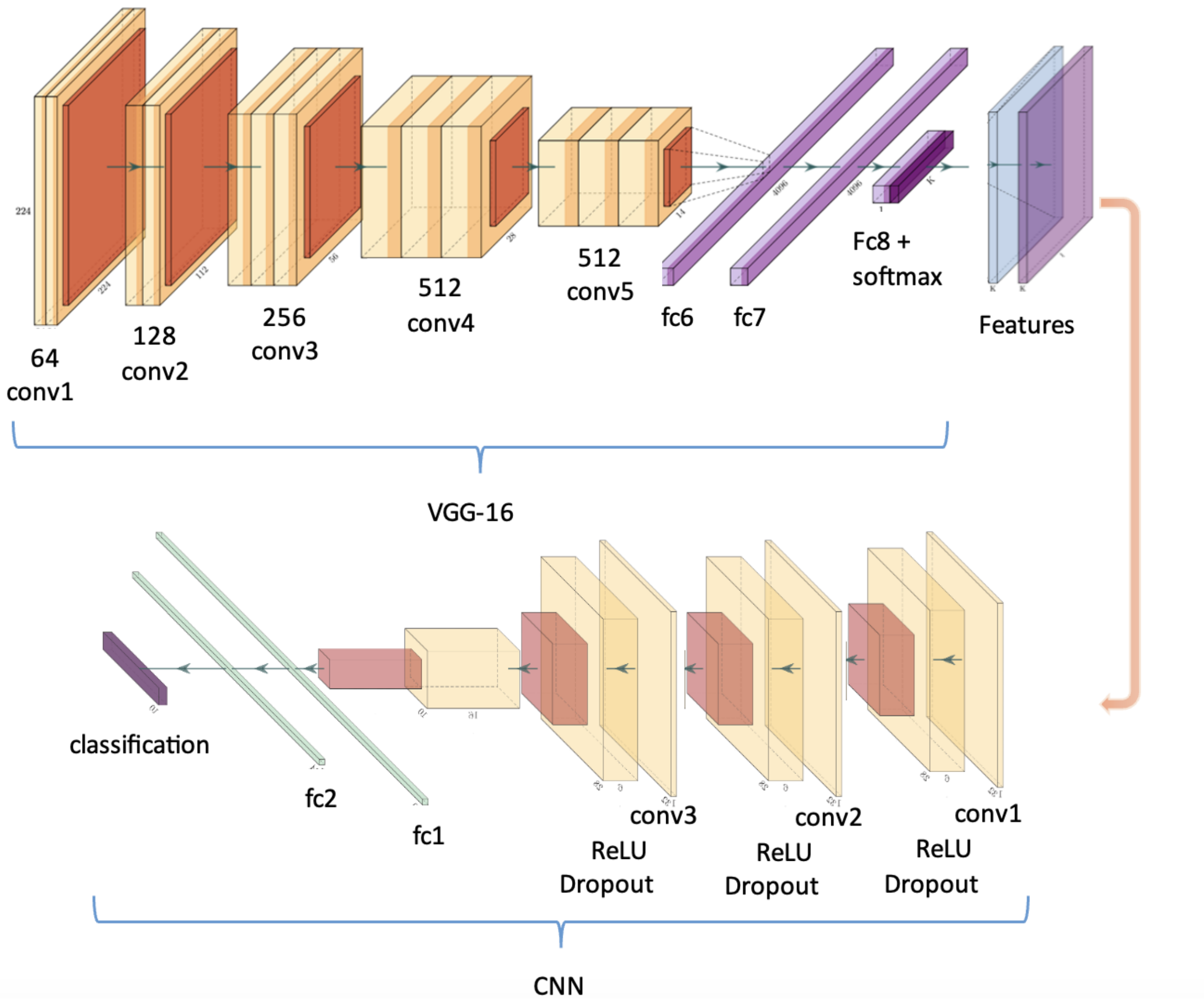

FIGURE 4. Architecture of the proposed model VGG16+CNN. Extracted features from VGG-16 are provided to CNN for classification.

Furthermore, the hybrid model's performance has the capacity to capture both global and local contextual information of the given input. VGG16's proficiency in recognizing global patterns is complemented by the CNN's capability at capturing local details within the Knee X-ray images. This integration potentially addresses the challenges posed by the complexity and variability of knee OA present in X-Rays, leading to a more refined and effective diagnostic approach compared to the standalone models. The success of the hybrid model underscores the potential benefits of combining diverse neural network architectures to enhance diagnostic capabilities in medical image analysis.

In the future, additional imaging modalities may complement knee X-Rays for assessing the severity of osteoarthritis. This integration is expected to enhance overall accuracy, enabling physicians to better comprehend the condition efficiently.

V. CONCLUSION

This research paper rigorously examines the effectiveness of various neural network architectures, including CNN, VGG16, VGG19, and ResNet50, in the detection of osteoarthritis (OA) and its severity using five different grades. Recognizing the class imbalance problem in the knee X-Ray dataset, the study applies data augmentation techniques to resolve this issue. The incorporation of data augmentation emerges as an important factor, contributing to enhanced accuracies across all models. These findings emphasize the importance of addressing class imbalance in medical datasets and underscore the efficacy of the proposed model in advancing the field of OA detection.

This research also introduces a novel hybrid model for knee osteoarthritis (OA) diagnosis using X-ray images, merging the strengths of VGG16 and CNN architectures. This innovative approach demonstrates a clear superiority over individual models, based on the complementary features of each architecture. In particular, the hybrid model justification=centering,margin=1cm

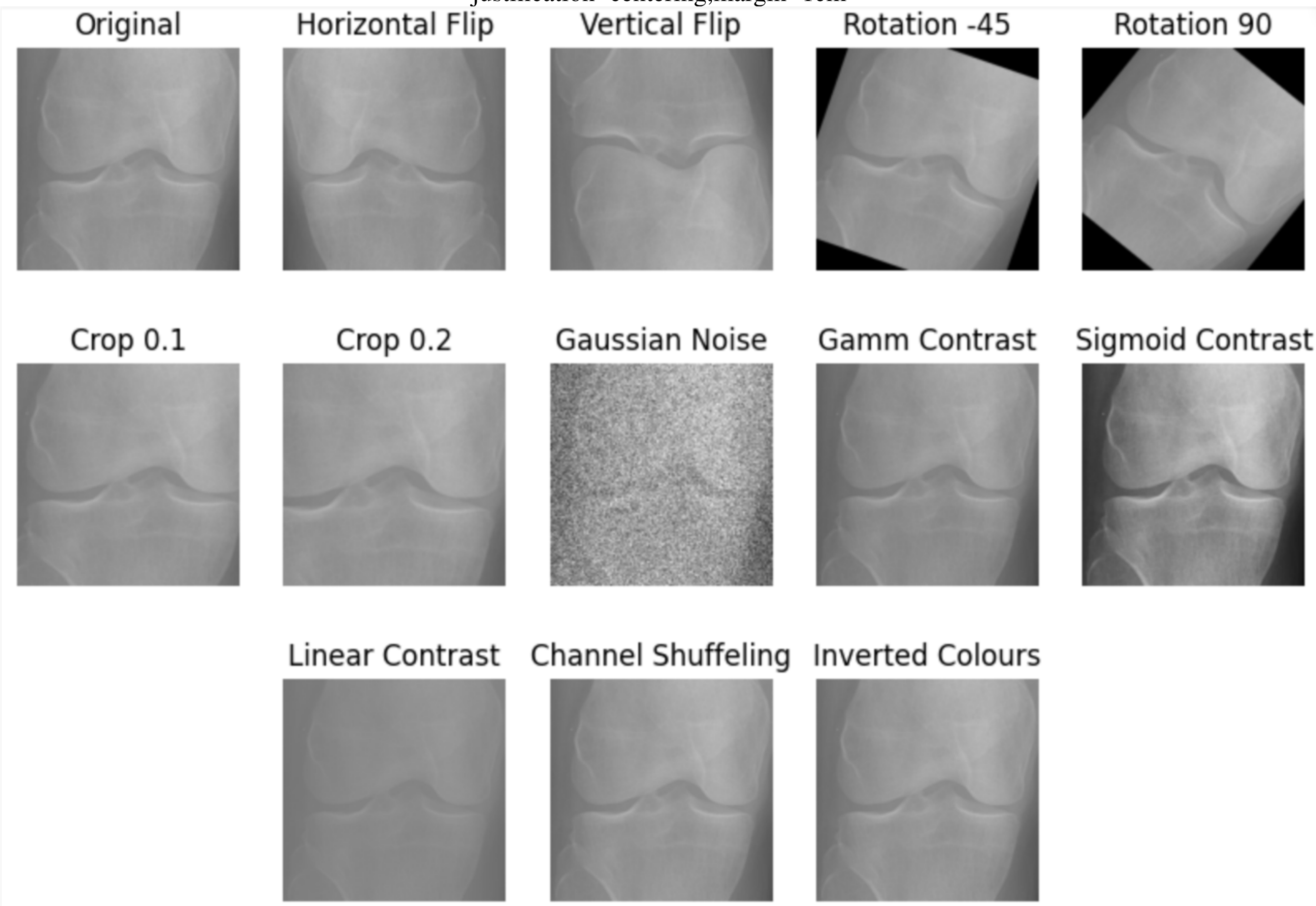

FIGURE 5. A sample original image and twelve augmented images generated from the original image

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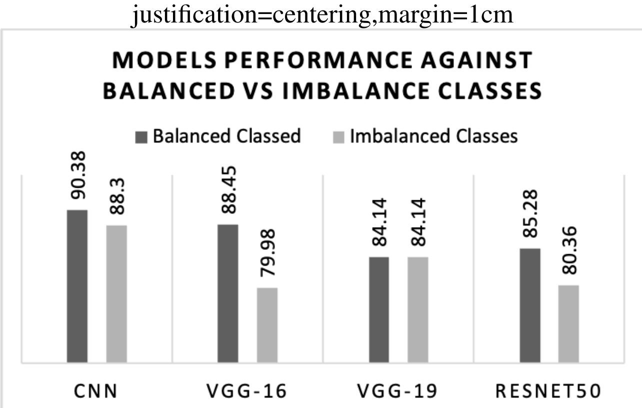

FIGURE 6. Performance of different models in the presence of class imbalance

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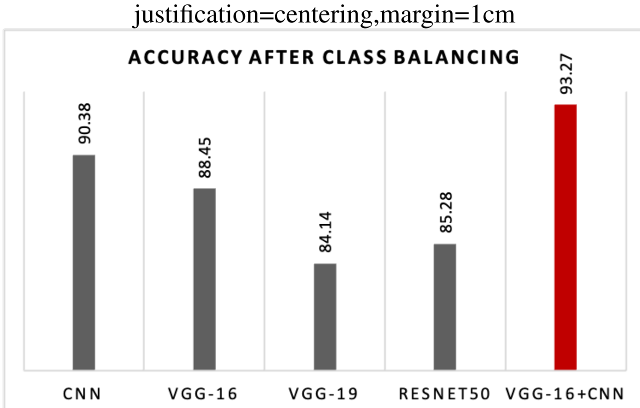

FIGURE 7. Performance comparison between proposed models and all the other models after class balancing

excels at capturing both global and local contextual information in knee X-ray images. This integration leads to a refined and effective diagnostic approach, surpassing the standalone models.

The key features of the study include:

- This study emphasizes on the critical role of data augmentation in improving model performance.
- It highlights the potential of the proposed model as a promising tool for accurate and reliable OA detection.
- This research contributes valuable insights to the evolving landscape of medical image analysis, emphasizing the importance of combining complementary strengths

for more effective diagnostic methods.

DECLARATIONS

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Data Availability: The dataset [28] used in this research is freely available.

Conflict of Interest: It is declared by the authors that there is no conflict of interest.

Code availability Code can be provided on request.

Authors' contributions SR worked on algorithm implementation and wrote the initial draft of the article. VG verified and analysed the results and improved article write-up.

REFERENCES

[1] A. S. Mohammed, A. A. Hasanaath, G. Latif, and A. Bashar, "Knee osteoarthritis detection and severity classification using residual neural networks on preprocessed x-ray images," Diagnostics, vol. 13, no. 8, p. 1380, 2023.

[2] J. H. Cueva, D. Castillo, H. Espinós-Morató, D. Durán, P. Díaz, and V. Lakshminarayanan, "Detection and classification of knee osteoarthritis," Diagnostics, vol. 12, no. 10, p. 2362, 2022.

[3] M. Cross, E. Smith, D. Hoy, S. Nolte, I. Ackerman, M. Fransen, L. Bridgett, S. Williams, F. Guillemin, C. L. Hill et al., "The global burden of hip and knee osteoarthritis: estimates from the global burden of disease 2010 study," Annals of the rheumatic diseases, vol. 73, no. 7, pp. 1323–1330, 2014.

[4] T. Janvier, R. Jennane, A. Valery, K. Harrar, M. Delplanque, C. Lelong, D. Loeuille, H. Toumi, and E. Lespessailles, "Subchondral tibial bone texture analysis predicts knee osteoarthritis progression: data from the osteoarthritis initiative: Tibial bone texture & knee oa progression," Osteoarthritis and cartilage, vol. 25, no. 2, pp. 259–266, 2017.

[5] L. Khedher, I. A. Illán, J. M. Górriz, J. Ramírez, A. Brahim, and A. Meyer-Baese, "Independent component analysis-support vector machine-based computer-aided diagnosis system for alzheimer's with visual support," International journal of neural systems, vol. 27, no. 03, p. 1650050, 2017.

[6] K. Kalo, D. Niederer, M. Schmitt, and L. Vogt, "Acute effects of a single bout of exercise therapy on knee acoustic emissions in patients with osteoarthritis: A double-blinded, randomized controlled crossover trial," BMC musculoskeletal disorders, vol. 23, no. 1, pp. 1–12, 2022.

[7] L. Shamir, S. M. Ling, W. W. Scott, A. Bos, N. Orlov, T. J. Macura, D. M. Eckley, L. Ferrucci, and I. G. Goldberg, "Knee x-ray image analysis method for automated detection of osteoarthritis," IEEE Transactions on Biomedical Engineering, vol. 56, no. 2, pp. 407–415, 2008.

[8] J. Abedin, J. Antony, K. McGuinness, K. Moran, N. E. O'Connor, D. Rebholz-Schuhmann, and J. Newell, "Predicting knee osteoarthritis severity: comparative modeling based on patient's data and plain x-ray images," Scientific reports, vol. 9, no. 1, p. 5761, 2019.

[9] P. Chen, "Knee osteoarthritis severity grading dataset," Mendeley Data, vol. 1, pp. 21–23, 2018.

[10] A. Tiulpin, J. Thevenot, E. Rahtu, P. Lehenkari, and S. Saarakkala, "Automatic knee osteoarthritis diagnosis from plain radiographs: a deep learning-based approach," Scientific reports, vol. 8, no. 1, p. 1727, 2018.

[11] J. H. Kellgren and J. Lawrence, "Radiological assessment of osteo-arthrosis," Annals of the rheumatic diseases, vol. 16, no. 4, p. 494, 1957.

[12] M. Tamoor, A. Naseer, A. Khan, and K. Zafar, "Skin lesion segmentation using an ensemble of different image processing methods," Diagnostics, vol. 13, no. 16, p. 2684, 2023.

[13] Y. S. Malik, M. Tamoor, A. Naseer, A. Wali, and A. Khan, "Applying an adaptive otsu-based initialization algorithm to optimize active contour models for skin lesion segmentation," Journal of X-Ray Science and Technology, no. Preprint, pp. 1–16, 2022.

[14] G. Nasreen, K. Haneef, M. Tamoor, and A. Irshad, "a comparative study of state-of-the-art skin image segmentation techniques with cnn," Multimedia Tools and Applications, vol. 82, no. 7, pp. 10 921–10 942, 2023.

[15] D. Albashish, R. Al-Sayyed, A. Abdullah, M. H. Ryalat, and N. A. Almansour, "Deep cnn model based on vgg16 for breast cancer classification," in 2021 International conference on information technology (ICIT). IEEE, 2021, pp. 805–810.

[16] C. B. Maior, J. M. Santana, I. D. Lins, and M. J. Moura, "Convolutional neural network model based on radiological images to support covid-19 diagnosis: Evaluating database biases," Plos one, vol. 16, no. 3, p. e0247839, 2021.

[17] M. Saeed, A. Naseer, H. Masood, S. U. Rehman, and V. Gruhn, "The power of generative ai to augment for enhanced skin cancer classification: A deep learning approach," IEEE Access, vol. 11, pp. 130 330–130 344, 2023.

[18] J. Antony, K. McGuinness, K. Moran, and N. E. O'Connor, "Automatic detection of knee joints and quantification of knee osteoarthritis severity using convolutional neural networks," in Machine Learning and Data Mining in Pattern Recognition: 13th International Conference, MLDM 2017, New York, NY, USA, July 15-20, 2017, Proceedings 13. Springer, 2017, pp. 376–390.

[19] S. M. H. Rizvi, A. Naseer, S. ur Rehman, S. Akram, and V. Gruhn, "Revolutionizing agriculture: Machine and deep learning solutions for enhanced crop quality and weed control," IEEE Access, 2024.

[20] P. Chen, L. Gao, X. Shi, K. Allen, and L. Yang, "Fully automatic knee osteoarthritis severity grading using deep neural networks with a novel ordinal loss," Computerized Medical Imaging and Graphics, vol. 75, pp. 84–92, 2019.

[21] A. Brahim, R. Jennane, R. Riad, T. Janvier, L. Khedher, H. Toumi, and E. Lespessailles, "A decision support tool for early detection of knee osteoarthritis using x-ray imaging and machine learning: Data from the osteoarthritis initiative," Computerized Medical Imaging and Graphics, vol. 73, pp. 11–18, 2019.

[22] C. Kokkotis, S. Moustakidis, E. Papageorgiou, G. Giakas, and D. Tsaopoulos, "Machine learning in knee osteoarthritis: A review," Osteoarthritis and Cartilage Open, vol. 2, no. 3, p. 100069, 2020.

[23] Y. Nasser, R. Jennane, A. Chetouani, E. Lespessailles, and M. El Hassouni, "Discriminative regularized auto-encoder for early detection of knee osteoarthritis: data from the osteoarthritis initiative," IEEE transactions on medical imaging, vol. 39, no. 9, pp. 2976–2984, 2020.

[24] C. W. Yong, K. Teo, B. P. Murphy, Y. C. Hum, Y. K. Tee, K. Xia, and K. W. Lai, "Knee osteoarthritis severity classification with ordinal regression module," Multimedia Tools and Applications, pp. 1–13, 2021.

[25] C. von Tycowicz, "Towards shape-based knee osteoarthritis classification using graph convolutional networks," in 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI). IEEE, 2020, pp. 750–753.

[26] Y. Wang, S. Li, B. Zhao, J. Zhang, Y. Yang, and B. Li, "A resnet-based approach for accurate radiographic diagnosis of knee osteoarthritis," CAAI Transactions on Intelligence Technology, vol. 7, no. 3, pp. 512–521, 2022.

[27] B. Guan, F. Liu, A. H. Mizaian, S. Demehri, A. Samsonov, A. Guermazi, and R. Kijowski, "Deep learning approach to predict pain progression in knee osteoarthritis," Skeletal radiology, pp. 1–11, 2022.

[28] S. Gornale and P. Patravali, "Digital knee x-ray images," Mendeley Data, vol. 1, 2020.

[29] A. Naseer, T. Yasir, A. Azhar, T. Shakeel, and K. Zafar, "Computer-aided brain tumor diagnosis: performance evaluation of deep learner cnn using augmented brain mri," International Journal of Biomedical Imaging, vol. 2021, 2021.

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