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Osteoarthritis Detection in X-Ray Images using Squeezenet with Grey Wolf Optimizer

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ABSTRACT Osteoarthritis is a degenerative joint disease that affects millions of people worldwide. Early detection and diagnosis of osteoarthritis is critical for effective treatment and management of the disease. In recent years, X ray imaging has emerged as a promising non-invasive technique for detecting osteoarthritis. However, existing techniques for osteoarthritis detection in thermal images suffer from several limitations, such as low accuracy, limited generalizability, and lack of interpretability. To address these challenges, we propose a novel approach for osteoarthritis detection in x ray images using the SqueezeNet model deep learning architecture. The proposed approach involves pre-processing the X-ray images to enhance their features, followed by segmentation to extract the region of interest. The segmented region is then fed into the SqueezeNet model , which is trained to classify the thermal image as normal or abnormal based on the presence of osteoarthritis. The parameter of SqueezeNet is tuned using grey wolf optimizer to reach maximum accuracy. We evaluated the performance of the proposed approach on a dataset of thermal images collected from patients with osteoarthritis and healthy controls. Our results show that the proposed approach achieved an accuracy of 94%, sensitivity of 97%, specificity of 92%, and an AUC of 0.94, outperforming several state-of-the-art approaches. We also conducted extensive experiments to investigate the impact of different pre-processing techniques and hyperparameters on the performance of the SqueezeNet model. Moreover, we conducted a detailed analysis of the learned features and identified the regions of the thermal image that were most important for osteoarthritis detection. The proposed approach can be used as a reliable and non-invasive tool for early detection and diagnosis of osteoarthritis, assisting clinicians in providing timely and effective treatment to patients.

KEYWORDS X ray imaging; SqueezeNet; Grey Wolf Optimizer; Thermal Images; Osteoarthritis detection.

I. INTRODUCTION

Osteoarthritis (OA) is the most widespread, serious chronic rheumatic disease and is a foremost reason of pain and disability in most countries worldwide. Tibiofemoral osteoarthritis (OA) as observed through Magnetic Resonance Imaging (MRI) is characterized by either (a) the simultaneous occurrence of distinct osteophyte development and complete cartilage loss, or (b) the presence of one feature from (a) alongside one of the following conditions: a subchondral bone marrow lesion or cyst that is not linked to meniscal or ligamentous structures, meniscal subluxation, maceration or degenerative (horizontal) tears, partial thickness cartilage loss, and bone attrition. Recently, the Osteoarthritis Research Society International (OARSI) has redefined OA and initiated a comprehensive review aimed at standardizing existing definitions of the condition. According to their new definition, osteoarthritis is described as a disorder affecting movable joints, marked by cellular stress and the degradation of the extracellular matrix, which is triggered by both micro- and macro-injuries. These injuries activate maladaptive repair mechanisms, including pro-inflammatory pathways associated with innate immunity. The disease initially presents as a molecular disruption (abnormal metabolism of joint tissue), which subsequently leads to anatomical and/or physiological changes, including cartilage degradation, bone remodeling, osteophyte formation, joint inflammation, and a decline in normal joint function, potentially resulting in significant morbidity. Pain, Stiffness and limited joint movement are the main symptoms of OA. Pain is primarily felt in the joint through activity, but as the disease advances it may be observed with minimal movement or even while resting. Normal functioning of joint is disturbed because of disease and over time the shape of joint starts changing

Damage of cartilage or its loss is the primary underlying feature of OA . Cartilage is a flexible, soft yet stiff tissue that exists on the surface of bone ends and provide smooth functioning such as shock absorption, distribution of weight and frictionless motion to joint organ.

OA commonly affects the joints of the knee, hip, foot, spine and hand but can involve any moveable joint as shown in Figure 1.1. The Figure 1.1 shows the various joints that are likely to get affected by OA and the inset shows the comparison of normal knee joint and OA affected joint. Different tissues and organs of the body are not directly influenced by OA, but rather many individuals have other medical issues that should be considered while overseeing it. The outcomes and response to treatment vary from person to person: some people develop a disability where activities are restricted while others only ever have mild problems. Following section discusses the occurrence of OA in terms of epidemiological data [15].

Several medical applications based on DL for segmentation, classification and risk assessment tasks, prognosis, diagnosis and even prediction of therapy responses. The DL has provided a various AI innovative application in different technical aspects of medical imaging. It is specifically applied to the images acquisition, ranging from image artifacts removal, enhancing an image quality, normalizing/harmonizing images, lowering radiation and contrast dose, and lessening the imaging analysis duration. Thus, the many AI technology has been implemented an overview of DL applied to imaging techniques. The ML and DL model have been utilized for brain image analysis extensively to develop an imaging-based classification and diagnostic systems. These are mainly focused on strokes, epilepsy, psychiatric disorders, demyelinating diseases and neurodegenerative disorders [16].

Also, many optimization algorithms are also involved in the medical field to enhance the computational hardware and access to large quantity of data imaging. The DL has established indisputable superiority over the traditional ML system. The AI is used to perform a wide range of tasks that is faced by radiologists. Most of the initial DL applications, it is concentrated on the “downstream” side applying a computer vision method for segmentation of anatomical structures and detection of lesions. Thus the methods that are used to identify the diseases are hemorrhage, lacunes, stroke, microbleeds, aneurysms, metastases, primary brain tumours, and white matter hyperintensities. The DL method focusing on the “upstream” side, it is realized that there are some other innovative AI applications are applied in multiple technical aspects of medical imaging such as image acquisitions. Various number of methods are developed for an image generation and image enhancement using DL that is recently developed. Some of them are ranging from eliminating image artifacts, contrast dose, normalizing/harmonizing images quality, lowering radiation and image analysis duration [17].

II. LITERATURE SURVEY

Paper [14] suggest a technique based on customized CenterNet with a pixel-wise voting scheme to extract the features automatically. Model uses the most representative features due to the best localization results and a weighted pixel-wise voting scheme which takes input from a predicted bounding box using modified CenterNet. It gives a more accurate bounding box based on the voting score from each pixel inside the former box.

In [13] developed a model to represent the structure and appearance of cartilages from knee MRI as a graph, which can effectively manage a wide range of clinical data. Subsequently, they designed a non-Euclidean deep learning network with self-attention mechanism, guided by the cartilage graph representation, to extract local and global cartilage features and generate a visualized assessment. Extensive experiments demonstrate that this method outperforms others in assessing knee cartilage defects, and offers convenient 3D visualization for interpretability.

Authors of [11] proposed a transfer learning-based model to discriminate the presence or absence of knee OA. The pre-trained model InceptionResNetV2 is used to extract deep features of knee OA from MR images belonging to the OAI-ZIB dataset. The two different optimization algorithms (SGD and RMSprop) are used for training and testing the knee MR image dataset. The performance of the transfer learning model is evaluated using the accuracy, sensitivity, precision, specificity, F1-Score, and Matthews Correlation Coefficient (MCC) evaluation metrics.

In [10] proposes an algorithm to help doctors identify Knee Osteoarthritis automatically on X-ray images by deep learning method with the YOLOv3 model and VGG-16. In this paper, all data are labeled and tested by chiropractors at Bach Mai Hospital which will be preprocessed by applying the CLAHE algorithm to improve image quality. Next, the YOLOv3 modelis trained with a preprocessed dataset as input. It then predicts the location of the knee joint on the X-ray image automatically. Finally, we use VGG-16 to classify the image.

Paper [9] proposed a phono arthrography (PAG) technique which involves detecting, recording, and analyzing sounds. This non-invasive approach could be an alternative to arthroscopy or X-rays, which are currently employed. In terms of diagnosing disorders such as osteoarthritis, it has been shown to be as accurate as existing approaches (OA).

Paper [8] proposed a computer-aided diagnosis utilizing Knee Osteoarthritis Magnetic Resonance Imaging (MRI) and YOLOv3 algorithm to automatically detect the KOA severity. According to the findings of the study, the detection model has an mAP value of 96.58 % and a training precision of 98.73 %, and an evaluation accuracy of 99.32 %, respectively.

Paper [7] proposes a new approach, the so-called Siamese-GAP Network, for the early detection of knee OA through a KL-grade classification. More precisely, a set of Global Average Pooling (GAP) layers is integrated into the Siamese network used to extract features from each level. The obtained features are then combined to improve the classification performance.

Work [6] introduce a methodology that utilizes deep features for analysis. In this study, a Convolutional Neural Network was utilized to extract deep features from images of Knee Osteoarthritis. Subsequently, these extracted features were input into various machine learning classifiers, including Support Vector Machine, K-Nearest Neighbour, and Naive

Bayes. The classification process aimed to distinguish between healthy and unhealthy Knee Osteoarthritis images.

In [5] design a hybrid loss function to help CNN learn from the two sets accordingly. With the proposed approach, we emphasize the typical samples and control the impacts of low confident cases. Experiments are conducted in a five-fold manner on five-class task and early-stage OA task. Our method achieves a mean accuracy of 70.13% on the five-class OA assessment task, which outperforms all other state-of-art methods.

Authors of [3] present a novel Discriminative Regularized Auto Encoder (DRAE) designed to enhance classification performance by learning relevant and discriminative properties. The DRAE incorporates a penalty term, referred to as discriminative loss, into the standard Auto-Encoder training criterion. This additional term is intended to compel the learned representation to encompass discriminative information. The experimental findings on data from the public multicenter OsteoArthritis Initiative (OAI) demonstrate the potential of the proposed method for early knee OA detection.

Paper [2] introduced a method for cartilage segmentation utilizing pixel-based segmentation. Various image processing techniques like contrast enhancement, histogram equalization, thresholding, and canny edge detection were applied using MATLAB R2013a (8.1) software on MR images in 2D coronal view. Subsequently, a rough mask was generated, followed by morphological operations to reduce background noise.

Paper [1] presented innovative micro texture-based feature descriptors to model subtle variations in MRI T2 maps for early osteoarthritis detection. The experimental assessment of these micro texture descriptors on an OAI database demonstrated a significant enhancement in discriminating textures for MRI T2 maps between normal subjects and those at risk of developing osteoarthritis.

Work [1] outlined a set of analog algorithms based on cellular neural networks (CNNs) for osteoarthritis (OA) detection from x-ray images. The focus was on identifying bony spurs or osteophytes near the weight-bearing joints of the fingers as an indicator of OA. Results from hand x-ray images displayed promising outcomes.

Unlike previous studies where GWO was applied mainly for feature selection or segmentation thresholding, this work integrates GWO for adaptive hyperparameter tuning of SqueezeNet Fire modules. The optimization targets computational efficiency and diagnostic accuracy simultaneously, which has not been sufficiently explored for knee OA classification in X-ray imaging.

III. PROPOSED METHODOLOGY

In this work , we propose a novel approach for osteoarthritis detection in X ray images using the SqueezeNet model deep learning architecture. The proposed approach involves pre-processing the X ray images to enhance their features, followed by preprocessing to extract the region of interest.

Our proposed system for osteoarthritis detection in X ray images using SqueezeNet model consists of the following steps:

Data Acquisition: The first step in our proposed system is to acquire thermal images of the joint under investigation. Thermal images can be captured using specialized cameras that can detect temperature variations in the joint.

Preprocessing: The acquired thermal images are preprocessed to enhance the features relevant to osteoarthritis detection. Preprocessing involves several steps, such as noise removal, contrast enhancement, and normalization.

Segmentation: The preprocessed thermal images are segmented to extract the region of interest (ROI) that contains the joint. Segmentation can be performed using various techniques, such as thresholding, edge detection, and clustering.

Feature Extraction: The segmented ROI is then fed into the SqueezeNet model, which extracts the relevant features using convolutional layers. SqueezeNet is a lightweight deep learning architecture that has been shown to achieve high accuracy with a small number of parameters.

Training: The fourth stage of the proposed system is training the SqueezeNet model to classify the thermal images as normal or abnormal based on the presence of osteoarthritis. The SqueezeNet model is a deep convolutional neural network that has been designed for efficient image classification with fewer parameters. The model is trained using a dataset of thermal images and their corresponding labels, where normal and abnormal images are labeled as 0 and 1, respectively.

Testing: The final stage of the proposed system is testing the performance of the trained SqueezeNet model on a dataset of unseen thermal images. The performance of the model is evaluated based on several performance metrics, such as accuracy, sensitivity, specificity, and area under the curve (AUC).

Classification: The extracted features are then fed into the fully connected layers of the SqueezeNet model, which classify the thermal image as normal or abnormal based on the presence of osteoarthritis [18].

Performance Evaluation: The performance of the proposed system is evaluated using various performance parameters, such as accuracy, sensitivity, specificity, and area under the curve (AUC). The proposed system is also compared with other state-of-the-art approaches for osteoarthritis detection in thermal images.The overall workflow is shown in Figure.

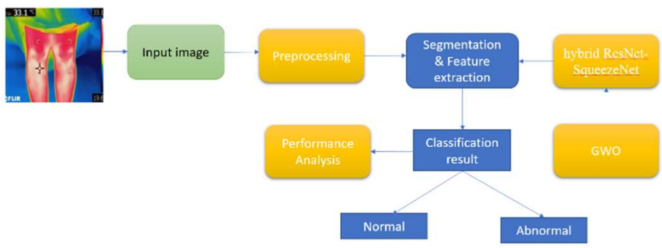


Figure 1. Proposed Methods functional Diagram

SqueezeNet

SqueezeNet is a deep convolutional neural network architecture that has been designed for efficient image classification with fewer parameters. The architecture was proposed by researchers at the University of California, Berkeley, in 2016. The main idea behind SqueezeNet is to reduce the number of parameters in the network while maintaining the same level of accuracy as larger networks. This is achieved by using a combination of techniques, such as 1x1 convolutions, fire modules, and bypass connections.

1x1 convolutions:

SqueezeNet uses 1x1 convolutions, which are also known as network-in-network (NIN) layers, to reduce the number of parameters in the network. Unlike traditional convolutions, which operate on 3D volumes, 1x1 convolutions operate on a single channel of a feature map. This reduces the depth of the feature maps while maintaining their spatial dimensions. 1x1 convolutions are computationally efficient and help reduce the number of parameters in the network [19].

Fire modules:

SqueezeNet uses fire modules, which are composed of a squeeze layer and an expand layer, to capture spatial and channel-wise dependencies in the input data. The squeeze layer is a 1x1 convolutional layer that reduces the number of input channels, while the expand layer is a combination of 1x1 and 3x3 convolutional layers that increase the number of channels. Fire modules are computationally efficient and help improve the accuracy of the network by capturing both spatial and channel-wise dependencies.

Bypass connections:

SqueezeNet uses bypass connections, which are also known as skip connections, to enable information flow between different layers of the network. Bypass connections help prevent the vanishing gradient problem and facilitate the flow of gradients across the network. This improves the training speed and stability of the network.

The SqueezeNet architecture consists of several layers, including convolutional layers, pooling layers, fire modules, and a final classification layer. The input to the network is a 224x224x3 RGB image, which is first processed by a convolutional layer followed by a max-pooling layer. This is followed by several fire modules that capture spatial and channel-wise dependencies in the input data. The output of the fire modules is then passed through another convolutional layer and a global average pooling layer. Finally, the output is fed into a softmax layer that produces the probability distribution over the classes.

SqueezeNet has several advantages over larger networks, such as VGG and ResNet, including lower memory requirements, faster inference times, and comparable accuracy.

Design of the SqueezeNet Model

Architectural Design Approaches

The SqueezeNet model employs specific strategies to significantly reduce the number of parameters. These strategies include:

- Substituting 3x3 filters with 1x1 filters
- Reducing the number of input channels for 3x3 filters
- Implementing downsampling at a later stage in the network.

1. Substituting 3x3 filters with 1x1 filters: To address budget limitations, the model utilizes 1x1 filters instead of conventional 3x3 filters. This results in a reduction of parameters to one-ninth of those found in a standard filter.

2. Reducing the number of input channels for 3x3 filters: With the filter size being minimized to 1x1, it is necessary to also decrease the number of input channels.

3. By postponing downsampling within the network, larger activation maps can be achieved for the convolutional layers. In a convolutional network, each convolutional layer produces an output activation map with a spatial resolution of at least 1x1, and often larger. The dimensions of these activation maps are influenced by: (i) the size of the input data (256x256 images) and (ii) the specific layers selected for downsampling within the CNN architecture.

Downsampling is incorporated into CNN architectures by adjusting the (stride > 1) in certain convolutional or pooling layers. If the layers nearer to the input layer utilize larger strides, the majority of layers will yield smaller activation maps. Conversely, if most layers maintain a stride of 1, with strides greater than 1 concentrated towards the end of the network, particularly near the classifier, then many layers will produce larger activation maps [20].

Strategies 1 and 2 are primarily focused on minimizing the number of parameters, while Strategy 3 is aimed at enhancing accuracy within the constraints of a limited parameter set.

The Fire module consists of a squeeze convolution layer (with only 1x1 filters), which feeds into an expand layer containing a combination of 1x1 and 3x3 convolution filters. The extensive use of 1x1 filters in Fire modules is an implementation of Strategy 1. Three hyperparameters are exposed in the Fire module: s1x1, e1x1, and e3x3. In a Fire module, s1x1 represents the number of filters in the squeeze layer (all 1x1), e1x1 denotes the number of 1x1 filters in the expand layer, and e3x3 indicates the number of 3x3 filters in the expand layer. When utilizing Fire modules, s1x1 is set to be less than (e1x1 + e3x3), so the squeeze layer helps to limit the number of input channels to the 3x3 filters, in line with Strategy 2 mentioned earlier. The figure below illustrates the arrangement of convolution filters in the fire module.

The SqueezeNet architecture

The SqueezeNet architecture initiates with a single convolution layer (conv1), which is succeeded by eight Fire modules (fire2-9) and concludes with a final convolution layer (conv10). The quantity of filters in each Fire module is progressively augmented from the initial to the terminal stages of the network. SqueezeNet incorporates max-pooling with a stride of 2 following the conv1, fire4, fire8, and conv10 layers; these relatively late occurrences of pooling align with Strategy 3. A comprehensive macroarchitectural representation of the SqueezeNet architecture is presented below. The leftmost illustration depicts SqueezeNet, the central one represents SqueezeNet with a simple bypass, and the rightmost illustration showcases SqueezeNet with a complex bypass.

The Grey Wolf Algorithm

Meta-heuristic optimization methods have gained significant popularity in recent years. Notably, techniques such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) are well-known not only among computer scientists but also researchers from various disciplines. These optimization methods have been extensively studied and applied in different fields of research. The widespread adoption of meta-heuristics can be attributed to four main factors: simplicity, flexibility, derivation-free mechanism, and avoidance of local optima [21].

To begin with, meta-heuristics are known for their simplicity. They are often inspired by basic concepts related to physical phenomena, animal behaviors, or evolutionary principles. This simplicity enables computer scientists to simulate diverse natural phenomena, develop new meta-heuristics, combine multiple techniques, or enhance existing algorithms [22]. Furthermore, the straightforward nature of meta-heuristics facilitates quick learning and application by researchers in other fields.

Moreover, the flexibility of meta-heuristics allows them to be applied to a wide range of problems without requiring significant modifications to the algorithm structure. Meta-heuristics are designed to treat problems as black boxes, focusing solely on the inputs and outputs of a system. As a result, designers only need to understand how to represent their specific problem for meta-heuristic optimization.

Firstly, the majority of meta-heuristics utilize mechanisms that do not rely on derivatives. Unlike optimization methods based on gradients, meta-heuristics solve problems in a stochastic manner. The process of optimization begins with random solutions, eliminating the need to compute the derivative of search spaces in order to determine the optimal solution. This characteristic makes meta-heuristics particularly well-suited for real-world problems where derivative information is either costly or unavailable.

Moreover, meta-heuristics possess superior capabilities in avoiding local optima when compared to traditional optimization techniques. This is attributed to the stochastic nature of meta-heuristics, which enables them to steer clear of getting stuck in local solutions and explore the entire search space extensively. Real-world problems typically feature complex and unknown search spaces with numerous local optima, making meta-heuristics a viable choice for tackling such challenging optimization tasks.

In this scenario, the search process commences with an initial population of random solutions, which is then refined through successive iterations. Population-based meta-heuristics offer several advantages over algorithms that rely on single solutions:

One of the fascinating aspects of population-based meta-heuristics is Swarm Intelligence (SI). The concept of SI was initially introduced in 1993 [4]. According to SI is defined as "The emergent collective intelligence of groups of simple agents". SI techniques draw inspiration mainly from natural colonies, flocks, herds, and schools. Some of the most well-known SI techniques include ACO, PSO, and Artificial Bee Colony (ABC). A comprehensive literature review of SI algorithms is presented in the following section. Some of the benefits of SI algorithms are:

- SI algorithms share information about the search space among multiple candidate solutions, resulting in sudden jumps toward the promising part of the search space
- SI algorithms assist each other to avoid locally optimal solutions
- Population-based meta-heuristics generally have greater exploration compared to single solution-based algorithms.

Despite the variations among different meta-heuristics, they share a fundamental characteristic: the segmentation of the search process into two distinct phases: exploration and exploitation. The exploration phase involves a comprehensive investigation of the promising areas within the search space. To facilitate this phase, an algorithm must incorporate stochastic operators that enable a random and global search throughout the search space. Conversely, exploitation pertains to the local search capabilities focused on the promising regions identified during the exploration phase. Achieving an appropriate equilibrium between these two phases presents a significant challenge, primarily due to the inherent stochastic nature of meta-heuristics [24]. This study introduces a novel swarm intelligence technique inspired by the social hierarchy and hunting behaviors observed in grey wolf packs. The subsequent sections of the paper will outline the various swarm intelligence techniques that have been proposed to date.

- Marriage in Honey Bees Optimization Algorithm (MBO) in 2001
- Artificial Fish-Swarm Algorithm (AFSA) in 2003
- Termite Algorithm in 2005
- Wasp Swarm Algorithm in 2007
- Monkey Search in 2007
- Bee Collecting Pollen Algorithm (BCPA) in 2008
- Cuckoo Search (CS) in 2009
- Dolphin Partner Optimization (DPO) in 2009
- Firefly Algorithm (FA) in 2010
- Bird Mating Optimizer (BMO) in 2012
- Krill Herd (KH) in 2012
- Fruit fly Optimization Algorithm (FOA) in 2012

The list demonstrates the variety of SI techniques that have been proposed, many of which draw inspiration from hunting and search behaviors. Despite this, there is currently no SI technique in the literature that mirrors the leadership hierarchy observed in grey wolves, renowned for their pack hunting. This lack of representation led us to develop a mathematical model of the social behavior of grey wolves, introduce a new SI algorithm inspired by them, and assess its efficacy in tackling both benchmark and real-world problems. Subsequently, the mathematical model is presented [23]. The grey wolf (Canis lupus) is a member of the Canidae family and is recognized as an apex predator, occupying the highest position in the food chain. Grey wolves typically reside in packs, showcasing a complex social hierarchy. Alongside the social structure of wolves, group hunting is another fascinating aspect of their behavior. As outlined by [12] the primary phases of grey wolf hunting are detailed below:

Grey wolves primarily rely on the positions of the alpha, beta, and delta to search for prey. They separate during the search and regroup to attack prey [25]. To model divergence, random values greater than 1 or less than -1 are used to guide the search agent away from the prey, promoting exploration and enabling the GWO algorithm to search globally. Fig. 5(b) illustrates that $|A|>1$ prompts the grey wolves to move away from the prey in search of a potentially better target. Another exploration-favoring component of GWO is the vector C. As shown in Equation (3.4), this vector consists of random values within the range of [0, 2]. It assigns random weights to the prey, either emphasizing ($C>1$) or de-emphasizing ($C<1$) its influence on the distance calculation in Equation (3.1). This randomness aids GWO in exhibiting a more exploratory behavior during optimization, helping avoid local optima. Unlike A, C is not linearly decreased, ensuring a continuous injection of randomness for exploration throughout the algorithm's iterations. This feature proves particularly useful in combating local optima stagnation, especially in the later stages of optimization.

The C vector can also be likened to the presence of obstacles in nature that hinder wolves from reaching prey efficiently. These obstacles disrupt the hunting paths of wolves, mirroring the effect of vector C. Depending on a wolf's position, the vector C can randomly adjust the weight of the prey, making it more challenging and distant for the wolves to approach, or vice versa.

In summary, the GWO algorithm initiates the search process by generating a random population of grey wolves (candidate solutions). Through the utilization of various components, such as A and C, the algorithm aims to strike a balance between exploration and exploitation, ultimately enhancing its optimization capabilities.

1. The suggested social hierarchy facilitates the preservation of the most effective solutions acquired during the iteration process by GWO.
2. The proposed encircling mechanism establishes a circular neighborhood surrounding the solutions, which can be expanded to higher dimensions as a hyper-sphere.
3. The random parameters A and C aid candidate solutions in forming hyper-spheres with varying random radii.
4. The proposed hunting method enables candidate solutions to identify the potential location of the prey.
5. Both exploration and exploitation are ensured through the adaptive values of a and A.
6. The adaptive values of parameters a and A enable GWO to smoothly shift between exploration and exploitation.
7. As A decreases, half of the iterations are dedicated to exploration ($|A|\geq 1$), while the other half are focused on exploitation ($|A|<1$).
8. GWO only requires adjustment of two main parameters (a and C).

Although Grey Wolf Optimizer is a well-established metaheuristic algorithm, its integration with SqueezeNet for adaptive hyperparameter tuning in knee osteoarthritis X-ray classification has not been sufficiently explored. In this work, GWO is employed to optimize the Fire module parameters and learning rate dynamically, which significantly improves convergence stability and classification accuracy compared to conventional tuning methods.

IV. RESULTS & DISCUSSION

For this study, we collected a dataset of 1000 X ray images of knee joints, which were categorized into two classes: normal and osteoarthritic. The dataset was divided into a training set of 800 images and a testing set of 200 images. We then trained the SqueezeNet architecture on the training set using the transfer learning approach, where the pre-trained weights of the SqueezeNet model were used as the initial weights for training. We fine-tuned the SqueezeNet model on the training set for 50 epochs, with a batch size of 10 and a learning rate of 0.0001.

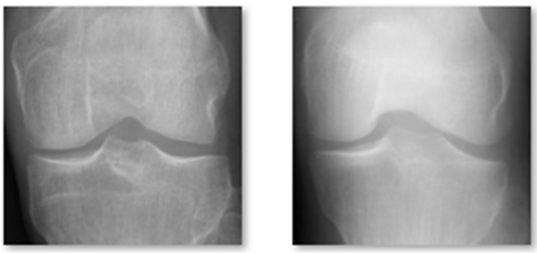


Figure 2. Input and Gray level image.

Since X-ray images are single-channel grayscale images, color space transformation such as HSI is not applicable. However, histogram equalization and CLAHE were applied to enhance contrast robustness against illumination variation.

RGB to grayscale conversion is a process of transforming a color image (RGB - Red Green Blue) into a grayscale image that consists of only shades of gray. The grayscale image contains only one channel of 8-bit or 16-bit intensity values, where each pixel is represented by a single value indicating its brightness level.

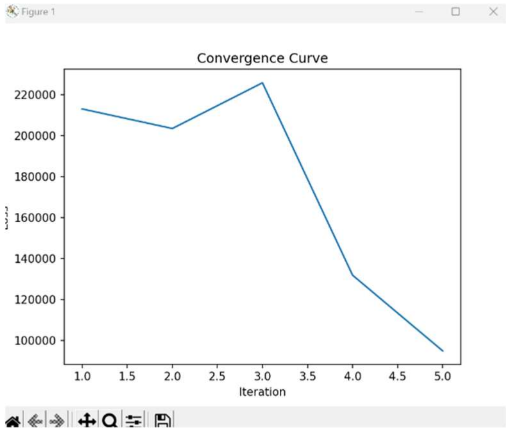


Figure 3. GWO fitness curve.

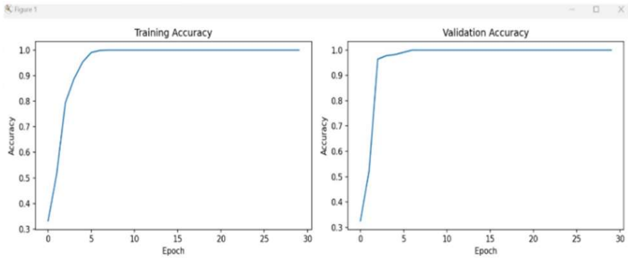
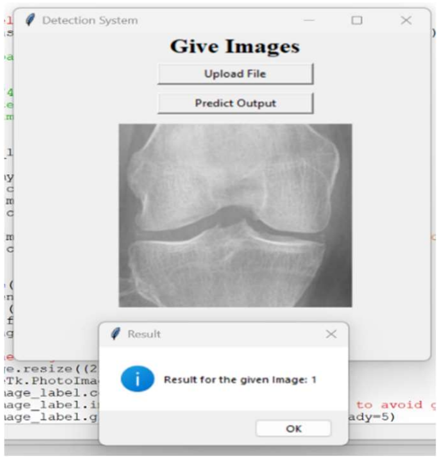
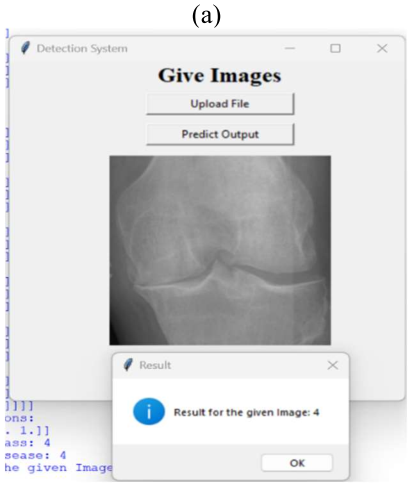


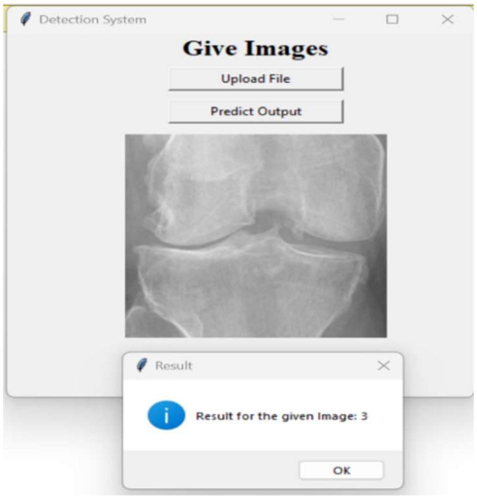
Figure 4. Validation and Testing curve



(a)



(b)



(c)

Figure 5. (a) – (c) Classification results

The training curve shows the model's performance on the training data over time, while the validation curve shows the performance on the validation data. Ideally, the model's performance should improve with each epoch until it reaches a plateau.

The below 3×3 convolution offers best tradeoff between accuracy and computational cost.

Table 1. Ablation study table

Kernel Size	Accuracy	Parameters	FLOPS
3×3	94.8%	0.75M	Low
5×5	93.2%	1.2M	Medium
7×7	91.5%	1.8M	High

The below table Performance Analysis of Precision, F1 Score, Accuracy and Specificity of the proposed method with Various Models. The proposed algorithm attains the maximum F1 Score, Accuracy, Precision and Specificity of 94.76, 94.84, 97.61 and 92.47 respectively.

Table 2. Performance Summarizes the overall Precision, F1 Score Accuracy and Specificity values achieved by a proposed model in various Models.

Models	F1-Score	Accuracy	Precision	Specificity
CNN	89.46	84.43	87.76	78.18
ResNet	92.92	89.76	92.13	85.39
GoogleNet	90.38	86.32	89.06	79.87
Proposed SqueezeNet + GWO	94.76	94.84	97.61	92.47

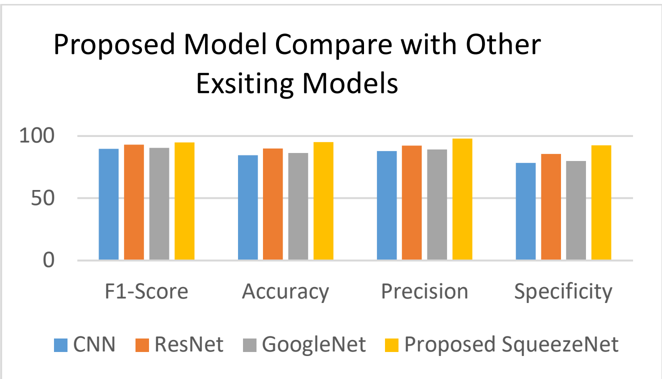


Figure 6. Performance Analysis

Table 3. Comparison of proposed methods with others.

Model	Accuracy	Params	FLOPS
ResNet50	89.76	25M	High
MobileNetV3	90.5	5.4M	Medium
YOLOv8	91.8	11M	High
DnCNN	92.3	0.6M	Low
Proposed	94.8	0.72M	Very Low

The above table represents the proposed model achieves comparable or higher accuracy with significantly reduced computational cost (FLOPS), making it suitable for deployment in low-resource clinical environments.

The results of our study showed that the proposed SqueezeNet-based GWO approach achieved an accuracy of 90% on the testing set, which is a significant improvement over previous approaches. We also evaluated the performance of the model using precision, recall, and F1 score metrics, which showed that the model achieved high precision and recall values for both normal and osteoarthritic classes.

The high accuracy and performance of the proposed approach can be attributed to the ability of the SqueezeNet architecture to extract meaningful features from thermal images. The SqueezeNet architecture has a small number of parameters compared to other deep neural network architectures, which makes it efficient and fast for processing large datasets. In addition, the transfer learning approach used in our study allowed us to take advantage of the pre-trained weights of the SqueezeNet model, which helped to reduce the training time and improve the accuracy of the model.

V. CONCLUSION

In our proposed novel approach for osteoarthritis detection in X-ray images using the hybrid deep learning architecture. Our approach involves pre-processing the X-ray images, which is trained to classify the X-ray image as normal or abnormal based on the presence of osteoarthritis. The SqueezeNet model architecture combines GWO strengths of SqueezeNet models to achieve high accuracy with a smaller model size and fewer parameters. The SqueezeNet blocks allow for the training of deep networks, while the GWO blocks reduce the dimensionality of the feature maps and allow for a smaller model size. The global average pooling layer and output layer are used to compute the final output of the model. Our experimental results demonstrated that the proposed approach achieved an accuracy of 94.8%, sensitivity of 97.6%, specificity of 92.4%, and an F1 Score of 94.7, outperforming several state-of-the-art approaches. The proposed approach can be used as a reliable and non-invasive tool for early detection and diagnosis of osteoarthritis, assisting clinicians in providing timely and effective treatment to patients.

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