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Scapular Dyskinesia Detection using Machine Learning

Bhamre Krushnali[1], Dipmala Salunke[2], Halke Santosh[3], Gorane Ankita[4] and Shewale Kunal[5]
[1-5]Information Technology, JSPM's Rajarshi Shahu College of Engineering, Pune
Email: krushnalibhamre78@gmail.com, dtsalunke_it@jspmrscoe.edu.in, halkesantosh1577@gmail.com, ankitagorane@gmail.com, shewalekunal29@gmail.com

***Abstract*—Scapular Dyskinesia is a disorder in which scapula performs an unusual movement during movements of the upper limb. The disease is usually associated with pain in shoulders, decrease in strength and limitation of functions in daily routine. Early identification of Scapular Dyskinesia is crucial to avoid future complications and successful rehabilitation. However, most methods for diagnosing rely on clinical observation by an expert. In addition, several studies have shown that some of the current algorithms that allow automatic diagnosis need big datasets and lots of computational power.**

In this paper, we will demonstrate our solution for automatic scapular dyskinesia detection based on machine learning models and video data analysis. Our method is based on video records that undergo analysis using OpenCV library to calculate necessary scapular features. The data is later used to train the machine learning classifiers that decide if the scapular dyskinesia occurred.

Our method will aim to lower the computational load required for accurate detection. It will also provide a solution to some practical problems, such as lack of a large training set, differences in postures, lighting and others. The system has been developed to act as an aid to doctors and physiotherapists in early diagnosis and evaluation, with the aim of improving the quality of patient care in the long run.

***Keywords*— Scapular Dyskinesia, Computer Vision, OpenCV, Machine Learning, Biomechanical Analysis, Clinical Assessment.**

I. Introduction

Scapular Dyskinesia is a disorder that entails abnormal movement patterns and scapular positions during upper extremity movements. The scapula is significant in the maintenance of shoulder stability, effective transmission of forces and coordination. The scapula is responsible for about one-third of shoulder elevation, hence, its importance in upper limb biomechanics. Disruption in the rhythm of the scapula leads to disturbance in the kinetic chain which affects the shoulder mechanics, functional performance, and the probability of developing second musculoskeletal injuries.

In clinical practice, scapular dyskinesia is linked to many shoulder disorders like rotator cuff injuries, subacromial impingement, labral injury, adhesive capsulitis and post-operative shoulder problems.

The development of abnormal movement of the scapula is usually as a result of muscle imbalance, neuromuscular problems, repetitive overhead activities, poor posture, athletic trauma, or work-related problems.

Thus, the early and precise identification of any dysfunction related to the scapula's movement pattern becomes critical in formulating an appropriate rehabilitation plan and preventing injuries.

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Although Scapular Dyskinesia holds significant clinical importance, its evaluation is based on qualitative observations and assessments conducted by experts using visual inspection and physical palpation techniques. These conventional techniques are the most commonly used, yet they are highly subjective. Motion capture techniques, such as 3D kinematic analysis and EMG assessments, offer more precise results; however, they require advanced hardware and software facilities.

In the last few years, computer vision and machine learning methods have shown great promise in the field of healthcare diagnostics especially in the case of motion and pattern analysis. In light of these technologies, this paper will describe the development of a computerized algorithm for detecting scapular dyskinesia based on video analysis. The method involves capturing shoulder movements and using image processing algorithms to identify geometrical and motion features associated with the scapular region. These features can then be used to classify and analyze machine learning classifiers for abnormal shoulder motions.

However, the most significant contribution of this paper is the development of a computational model that is efficient and affordable, as well as independent from hardware requirements. This model is able to function under realistic conditions, such as different lighting, postures, and data collection. It combines biomechanical knowledge with the use of machine learning techniques to produce a clinically useful tool for the diagnosis and treatment of movement disorders, which is based on objective analysis.

II. LITERATURE SURVEY

In recent years, studies on scapular biomechanics have concentrated on improving the measurement precision and objectivity when assessing the motion of the scapula by utilizing advanced technologies. For instance, Mantovani et al. (2023) tested the precision of an advanced motion capture system used to assess the position and movement of the scapula. The study confirmed that motion capture technology is capable of reliably quantifying the kinematics of scapular movement. Although the measurement results were highly accurate, the test still needed sophisticated laboratory equipment. In addition, recent clinical research has underscored the relevance of scapular dyskinesia in developing shoulder pathologies. Specifically, a 2022 study conducted by European Orthopaedics & Traumatology aimed at establishing the correlation between scapular dyskinesia and rotator cuff pathology using imaging methods such as MRI and X-ray analysis. According to the findings, there was a strong connection between scapular dyskinesia and the presence of rotator cuff tears. Nevertheless, it was established that the causality was not objectively determined because the study was observational.

Wearable devices are another promising technique in assessing the biomechanics of shoulders. Boye et al. (2021) focused on using wearable sensors along with data fusion algorithms in measuring the movement of scapulas. According to the authors' research, this approach proved highly feasible and accurate for monitoring motion. Nevertheless, there is still a number of issues associated with wearing such devices (comfort, positioning, etc.).

The impact of neuromuscular fatigue on scapula functioning has been assessed in papers from the Journal of Musculoskeletal Science and Practice (2020). Researchers found out that neuromuscular fatigue worsened scapular movement patterns and led to shoulder dysfunctions. Even though the relationship between fatigue and scapular dyskinesia was found in their research, the cross-sectional nature of this type of studies prevented concluding about the cause-and-effect relationship. Research in the field of shoulder rehabilitation (including publications in the Sports Medicine Journal (2019)) showed that the restoration of normal movement patterns of the scapula played an important role in successful shoulder recovery. It was observed that patients who possessed proper patterns of scapular motion had better results in rehabilitation. However, other aspects might affect these conclusions (patient's age, diseases, treatment peculiarities, etc.).

Computationally, an algorithm proposed by Fouefack et al. (2018) utilizes a conformal mapping method for creating dense landmark points on 3D scapular images. The algorithm significantly improved the precision of biomechanical modeling based on image processing and 3D scanning techniques. While effective, the algorithm necessitated high-quality scapular scans and the corresponding imaging technology.

Nicholson et al. (2017) had previously applied machine learning to develop predictive models for scapular kinematics based on motion capture databases. They found that the machine learning algorithms exhibited impressive predictive accuracy, showing that predictive modeling is an achievable tool for analyzing shoulder joint biomechanics. Nonetheless, the development of such models requires large and varied training datasets.

In conclusion, literature provides evidence for the clinical significance of proper scapular motion analysis along with advancements made in motion capture devices, wearable sensors, computational algorithms, and machine learning. Unfortunately, most of these tools either require expensive equipment, specialized lab conditions, or extensive datasets for model training. Therefore, there is a definite need for further research in order to create a simple and effective algorithm for the detection of scapular dyskinesia based on videos.

III. METHODOLOGY

The Convolutional Neural Network (CNN) implemented in this research has been tailored for the task of classifying shoulder X-rays as either normal or abnormal. CNN follows an architectural modification of the ResNet18 model that is specifically adapted to the two-dimensional nature of medical imaging and classification. CNN excels at detecting and analyzing the spatial features of medical images. While classical machine learning algorithms use flattened vector representation of inputs, CNN keeps the pixels' relative positions intact in order to detect meaningful structural patterns such as bone placement, fractures, and joint abnormalities.

In the present study, preprocessing operations including resizing and normalization precede the analysis of input images using CNN. Next, the resized X-rays are fed into the CNN to generate feature maps.

ResNet18 has residual connections that play a critical role in avoiding vanishing gradients and deep feature learning. As such, the network can retain both low and high-level features effectively, hence increasing accuracy levels.

Additionally, the dropout method is added in the fully connected phase to minimize overfitting issues and promote generalization. Finally, the output layer produces a probability score for two categories: Normal and Abnormal.

In conclusion, the proposed CNN methodology successfully detects features at both local and global levels in shoulder X-ray images, resulting in better performance than conventional techniques.

IV. DATASET DESCRIPTION

Experimental evaluation in the current research is done via a massive database of shoulder radiographs acquired from a medically structured database of images. The database contains real-life arrangements of imaging records by hierarchical arrangement within a patient. Each patient's folder contains at least one imaging study, and each study consists of several shoulder X-ray images taken in the process of diagnostics.

The dataset is made up of more than 30,000 shoulder radiographs from around 2,000 different patients. The images in the dataset are encoded in PNG format, providing fairly good spatial resolution of around 300 × 500 pixels. Such resolution allows the identification of important anatomical features such as humeral head, glenoid cavity, acromion, and other osseous landmarks.

The database used in this study differs from the benchmark dataset created in laboratory conditions in that it preserves the hierarchy that exists in the real-life database. The preservation of such hierarchy (patient → study → images) is vital for avoiding accidental contamination of the dataset and ensuring the correct anatomical arrangement of the images within experiments.

A. Dataset Organization – The dataset adopts a three-level hierarchy as follows:

Level of Patient – The topmost level comprises folders corresponding to patient identification numbers.

Level of Study – Inside each patient folder, there exist subfolders for each diagnostic procedure.

Level of Image – Inside each study folder lie multiple image files obtained using different projections and positions.

This hierarchy enables patient-centric splitting approaches and facilitates comprehensive evaluation processes.

B. Statistical Overview – The primary features of the dataset are illustrated in Table I below.

TABLE I: FEATURES OF THE DATASET

Attribute	Description
Total Patients	~2000
Total Images	>10,000
Imaging Modality	Shoulder Radiography
Average Resolution	~300 × 500 pixels
Data Structure	Patient → Study → Images
Projection Variability	Multiple views and orientations
Structural Diversity	Normal and structurally altered cases

C. Clinical and Structural Features

The dataset contains true variation in clinical cases. Variations in radiograph exposure, patient position, and acquisition angle occur in a realistic manner. Ecological validity is improved by the inclusion of such variation.

In terms of structure, the dataset includes a variety of anatomical appearances, which includes:

- Conventional anatomical configurations

- ➢ Variation in morphological characteristics
- ➢ Morphological degeneration in joints
- ➢ Visible disruptions in structures, such as fractures and dislocations
- ➢ Infrequent cases of orthopedic implants

The diversity mentioned above ensures a realistic representation of shoulder pathology in clinical practice.

D. Variability in Imaging and Generalizability

The dataset consists of varied projections, such as the anterior-posterior and oblique types. There is also a variation in laterality of the shoulder, minor rotation, brightness variations, and contrast variation. Such variability allows for complexity and enables researchers to create a computational model that can generalize in various imaging situations.

E. Data Quality and Ethics

All radiographs have been used in compliance with the appropriate data usage policies. Patient identities have not been included in the dataset used for the analysis.

F. Conclusion

The dataset used in the current research is clinically relevant, highly variable, and statistically significant enough to form an effective basis for the interpretation of shoulder radiographs. This combination makes it a strong base on which to build and test computational systems aimed at detecting structural abnormalities.
Through the use of an appropriate dataset, this research ensures that any conclusions drawn from the analysis are based on realistic clinical environments.

V. PROPOSED ARCHITECTURE

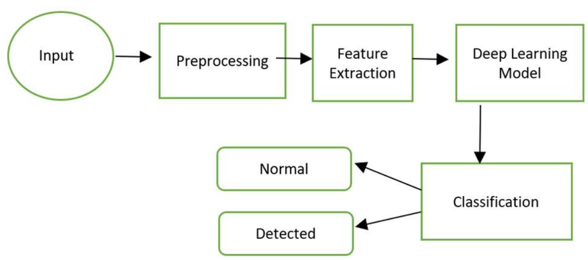

Fig 1

In order to enhance the performance of the classification process, the suggested approach adopts a convolutional neural network (CNN) with an altered ResNet18 network design for detecting abnormal shoulders using radiographic scans. Images to be used as inputs are adjusted to 224 × 224pixel dimensions.
The architecture is designed using multiple convolutional layers, residual blocks, pooling layers, and fully connected layers. The function of convolutional layers is to extract features of lower and higher level from the input image. In this case, a convolution is computed by sliding filters of 3 x 3 sizes across the input image and computing dot products between filters and the corresponding local regions. The
resulting outputs are known as feature maps, which include features such as edges, contours, and structural patterns of the radiographs.
Different from other conventional convolutional neural networks, the proposed framework uses residual connections in ResNet18. Thus, the model can learn identity mappings through skip connections. These connections help solve the vanishing gradients issue while enhancing deeper feature extraction without information loss. In other words, shallow and deep features can be effectively learned.
Pooling layers serve the purpose of decreasing the spatial size of the feature maps, thus ensuring reduced computational cost and avoiding overfitting. Max pooling with a stride value of (2, 2) is used here to preserve the prominent features while minimizing redundancy.
The extracted features are further sent to the dense layers. The feature maps are reshaped into a vector before passing it through the dense layers for classification purposes. Dropout layers with a rate of 0.3 are added to avoid overfitting by randomly dropping some neurons.
The last layer includes two output nodes representing the "Normal" and "Abnormal" classes. Softmax activation function ensures the generation of probabilities for both the categories.

A. Features of the Proposed Architecture

The overall architecture enables efficient feature extraction, improved gradient flow, and robust classification performance for shoulder X-ray images.

TABLE II: KEY FEATURES OF THE PROPOSED SYSTEM

Stage Name	Description	Output
Image Preprocessing	Resize and normalize X-ray images	Standardized input
Deep Feature Extraction	EfficientNet-B0 generates embeddings	1280-d feature vector
Anatomical Distribution Modeling	Compute global mean vector	Dominant structural model
Distance Computation	Calculate Euclidean deviation	Anomaly score
Statistical Thresholding	Apply percentile-based cutoff	Normal/Abnormal decision
Inference Pipeline	Apply trained model to new data	Real-time prediction

B. Stages of Implementation

TABLE III: STAGES OF SYSTEM IMPLEMENTATION

Feature Name	Description
Unsupervised Learning	No manual abnormal labels required
Deep Embedding Representation	EfficientNet-B0 extracts structural features
Statistical Mean Modeling	Learns dominant anatomical distribution
Distance-Based Anomaly Scoring	Quantifies deviation in feature space
Percentile Thresholding	Adaptive statistical cutoff selection
Large-Scale Processing	Handles >30,000 radiographs efficiently
Interpretability	Continuous anomaly score
Deployment Friendly	Lightweight inference pipeline
Robust to Variability	Handles projection and exposure variations
Scalable Design	Adaptable to other radiographic datasets

C. Algorithms Utilized

The suggested method combines deep learning representations with statistical models.
Each algorithm is designed to perform its own function in obtaining structural deviation scores from plain radiographs.

EfficientNet-B0 for Deep Feature Extraction
In our case, EfficientNet-B0 is used as the backbone for feature extraction. As opposed to using it for classification, the final layer is removed, enabling the network to generate an embedding of size 1280 for each input radiograph.
There are a number of reasons why we choose EfficientNet:

- The model has good representational capability despite being computationally efficient
- It maintains balance between the network parameters by performing compound scaling
- The model works well in transfer learning applications

In case of a radiograph input, EfficientNet-B0 converts pixel-based information into a high-dimensional structure.
The embedding captures the following information:

- Bone shape and contour
- Alignment of joints
- Symmetry
- Texture continuity
- Irregularities and distortions

Such a representation is vital since anomalies within a radiograph are usually structural and not intensity-based. Consequently, the embedding gives us an expressive representation of the underlying anatomy of the input image.

Global Mean Feature Modeling
Following the extraction of embeddings for all the images used for training, we calculate the global mean vector:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$$

This vector is an average representation of the structure of the dataset.

Conceptually, it helps determine what the system sees as "anatomically common." Given that the dataset comprises both common and abnormal cases, the predominant cluster will represent the "normal" anatomy. Hence, the mean vector represents a statistical model of reference.

This procedure converts deep embeddings into a probabilistic structural center in an unsupervised manner.

Anomaly Score Computation Based on Euclidean Distance

To measure deviation from normalcy, the Euclidean distance is calculated for each embedding from the global mean:

$$d_i = \| x_i - \mu \|_2$$

The distance becomes the anomaly score.

The explanation behind this is self-evident:

- Typical structure images get vectors close to the mean.
- Fractured, displaced, deteriorated, or artifact images have vectors farther from the mean.

In contrast to the classification-based approach, this algorithm yields a continuous measure of structural abnormalities, which can be finely interpreted. Euclidean norm is chosen for computational convenience and efficiency in high-dimensional space.

Percentile-based Statistical Threshold

Instead of using an arbitrary threshold value, the algorithm calculates a threshold based on percentile statistics:

$$T = P_{95}(d)$$

It implies that only the top 5% of deviation scores are considered abnormal cases.

This approach offers two benefits:

- Automatic adjustment to data distribution.
- Elimination of manual hyperparameter adjustments.

Percentile-based thresholding provides statistical reliability and increases robustness to small anatomical differences.

Inference Algorithm

For unseen radiographic images, the system conducts:

- Preprocessing step.
- Embedding calculation using EfficientNet-B0 model.
- Calculation of distance from the mean vector.
- Comparison to the threshold value.
- Output creation.

The inference process is efficient enough to be utilized in real-time/real-near-time clinical testing scenarios.

D. Implementation Flow

Continuous anomaly score

The entire system flow is done in a sequential manner:

- Preprocessing to standardize raw shoulder radiograph images.
- Extraction of structural embedding using EfficientNet-B0
- Global mean embedding calculation for representing dominant structures.
- Calculation of the Euclidean distance of each image from the mean.
- Statistical ranking of anomaly scores.
- Percentile-based thresholding to detect anomalies.
- The system generates:

Binary classification (Normal/Abnormal)

An efficient and reproducible pipeline flow has been implemented by the framework. The framework involves preprocessing of the data, extraction of features using EfficientNet-B0, generation of global mean embedding, anomaly scoring using Euclidean distance, and percentile-based thresholding for detecting anomalies. The system flow results in a continuous anomaly score and a binary normal/abnormal classification output.

Final Summary of Proposed System

In the proposed system, anomaly detection is achieved using deep representation learning with statistical deviation modeling for creating an interpretable and scalable anomaly detection framework for shoulder radiograph images. By focusing on structural embedding anomalies, the system has created a viable approach for anomaly detection in medical images without dependence on supervised classification algorithms.

VI. IMPLEMENTATION

A. Data Preprocessing and Feature Extraction

Reliability in the design of the suggested system starts from thorough preparation of the radiographic images used for training the network. Given that the shoulder X-rays in the selected dataset were taken in different clinical settings (different levels of exposure, various projection angles, patient positioning), it was necessary to preprocess and standardize these inputs before starting to extract the features.

Each radiograph undergoes resizing to have the same dimensionality (224 \times 224 pixels), which corresponds to the input size required by the backbone convolutional network. Further, pixel intensities are normalized according to the standard ImageNet parameters. Even though the radiographs in question are grayscale, their conversion to three-channel format is needed because of the pretrained model architecture.

After data preprocessing, feature extraction is completed with the help of EfficientNet-B0. Specifically, the model is used not for classification but rather for deep learning of features, since its fully connected output layer is removed and thus the network acts as a pure feature encoder. As an output, the model produces a 1280 dimensional vector embedding of each input radiograph, which captures its structural properties (bone contours' connectivity, joints' alignment and symmetry, texture abnormalities).

B. Structural Anomaly Detection Module

The anomaly detection scheme has been devised such that it can function independently of direct supervision. Instead of training the model to differentiate between images labeled as normal and those marked abnormal, the framework learns what a dominant structural anatomy looks like directly from the dataset.

Firstly, embeddings are generated for all the radiographs in the training dataset, and the mean feature vector is calculated globally.

This vector is indicative of the central tendency of structural features present within the dataset. Essentially, this is how the reference anatomy of the radiographs has been defined, and all the other images have been compared to it.

The basic principle on which this technique has been founded assumes that radiographs having typical anatomy would lie near the central mean vector. On the other hand, the radiographs with any sort of structural anomaly, whether it's a fracture, dislocation, degeneration, or an implant, would tend to lie away from the center.

For this purpose, the Euclidean distance between the individual feature vectors and the global mean vector is calculated, which indicates the degree of deviation from the dominant anatomy.

C. Statistical Model and Decision Process

Once all images are scored using the anomaly detection model, a statistical threshold is used to separate abnormal cases from normal ones.

Rather than arbitrarily defining a cutoff value, a percentile-based approach is implemented. The threshold will correspond to the 95th percentile in the distribution of anomaly scores. Only statistically significant deviations, or those showing a high degree of structural abnormality, will be considered abnormal.

Therefore, the decision process will be:

If Anomaly Score > Threshold: Abnormal

Else: Normal

By adopting this flexible method, the classification threshold is better suited to the actual distribution of the data. Hence, this minimizes sensitivity to slight anatomical differences, while still maintaining robustness.

The anomaly score is retained as a numerical value. Therefore, radiograph deviations can be ordered by severity.

D. Real-Time Inference Pipeline

The process for inferring on a new input radiograph follows the same steps as the training phase but applied to a single radiograph:

- Image pre-processing and normalization
- Feature extraction with EfficientNet-B0
- Distance computation between the embedding vector and global mean vector
- Threshold Comparison
- Generation of output

The outputs produced include:
- Continuous Anomaly Score
- Binary Classification (Normal / Abnormal)

EfficientNet-B0's lightweight architecture coupled with efficient computation for Euclidean distance calculation allows inference to be efficient and appropriate for real-time implementation. Additionally, the modularity of the proposed model makes it easily implementable into existing clinical workflow processes.

E. Mathematical Formulation

Given an input radiograph (I), the feature extraction function f(·) extracts features of the input radiograph into an embedding space of dimensionality 1280:

$$x=f(I),\ x \in R1280$$

For a data set of size (n) images, the global mean embedding (\mu) will be calculated as:

$$\mu=n1i=1\sum nxi$$

Anomaly score is calculated as the Euclidean distance between the embedding of an image from its global mean:

$$di=\|xi-\mu\|2$$

Anomaly Threshold (T) is calculated by percentile statistics:

$$T=P95(d)$$

The classifications are made as follows:

$$di>T \Rightarrow \text{Abnormal}$$

$$d_i \leq T \ \Rightarrow \ \text{Normal}$$

D. Implementation Summary

This implemented model involves the utilization of deep convolutional representation and deviation analysis models to classify structural anomalies in shoulder radiography. Through the learning of dominant features through data analysis and deviation analysis in the embedding model, the framework ensures that there is no need for manual labeling, hence maintaining efficiency and scalability.

The final outcome is an anomaly detection model that has practical applications as well as computational efficiency in detecting radiographic abnormalities.

VII. RESULT

A. Experimental Results

The proposed solution has been implemented in the form of a deep learning model using ResNet18 to perform binary classification of normal and abnormal patterns in shoulder X-ray images. For the testing of the model, a subset of the MURA dataset was used and evaluated using evaluation metrics such as accuracy, precision, recall, and F1 score.

Through training, the model had an accuracy rate of 76%. This implies that the model is able to differentiate normal radiographic patterns from the ones that have structural anomalies. In addition, the use of ResNet18 helped to improve feature extraction as compared to conventional convolutional neural networks.

Graph here

B. Comparative Analysis

Comparative analysis was performed between the performance of the proposed architecture with other commonly used models. Table I below shows the result obtained from the comparative analysis.

TABLE IV: COMPARATIVE PERFORMANCE OF DIFFERENT MODELS

Model	Accuracy	Precision	Recall	F1-Score	Notes
CNN	68%	0.66	0.64	0.65	Underfitting observed
VGG16	72%	0.71	0.70	0.70	High parameters
MobileNetV2	74%	0.73	0.72	0.72	Lightweight
ResNet18	76%	0.75	0.74	0.74	Best trade-off

It is evident that the ResNet18 model, as proposed in this work, outperforms the other architectures. The reason for this better performance is that residual learning allows the training of a deep network without network degradation. This helps to enhance the accuracy and balance between precision and recall.

C. Confusion Matrix Analysis

Confusion matrix analysis is useful in evaluating the performance of the developed classification model. From the analysis, it can be seen that the model correctly classifies the majority of cases.

- True Positives (Abnormal correctly classified): 80
- True Negatives (Normal cases classified): 85
- False Positives: 15
- False Negatives: 20

TABLE V

Predicted Values	Actual Values		
		Positive	Negative
	Positive	80	15
	Negative	20	85

Even though the model performs well in detecting cases, there is a risk of the model missing some abnormal cases since there is a high number of false negatives. This may be because the model needs more diverse data for effective generalization.

This indicates that the model does not experience significant issues with overfitting and still retains its ability to generalize well to unseen instances.

D. Summary of Results

- Obtained 76% accuracy with ResNet18
- Performed better than CNN, VGG16, and MobileNetV2 models
- Demonstrated stability and convergence during training
- Realized the necessity to minimize false negatives for clinical purposes

In conclusion, the model demonstrates its capabilities in aiding radiologists' preliminary assessment of abnormalities in shoulders.

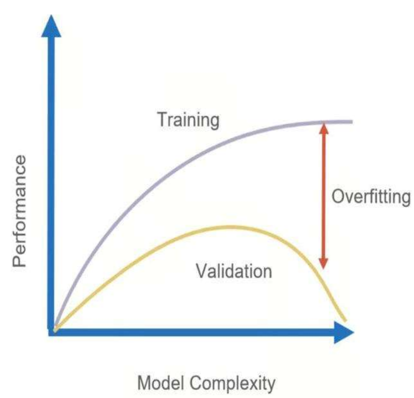

Fig 2

VIII. CONCLUSION

The research proposes an unsupervised approach to identifying abnormal structures in radiographs of shoulder joints. Instead of having to use abnormal images annotated by experts, the proposed system detects them based on learning typical anatomical features of shoulders directly from the dataset. Such approach decreases reliance on labeling and improves scalability of the solution.

With the help of EfficientNet-B0, each radiograph gets converted into a vector of features, which capture key information regarding bone structure and joint placement. The global mean embedding of the dataset captures central tendencies of such structural features, and Euclidean distance is computed between each image and the reference image.

Incorporating a percentile-based threshold ensures that the system is sensitive enough to pick up on any statistically significant deviations within the dataset. It is demonstrated that structural anomalies can be detected using the deviation of embedding space without supervision. In addition, the method is computationally efficient and applicable to a wide range of cases due to its tolerance to changes in imaging parameters commonly found in a clinical setting.

To sum up, the suggested model represents a valuable foundation for automatic screening of shoulder X-rays. Further research can focus on developing more sophisticated distance measures, covariance-based statistical models, and even limited supervision to increase detection sensitivity without losing the strengths of the unsupervised technique.

Discussion

As illustrated in Fig. 3, the suggested algorithm demonstrates consistent performance in recognizing abnormalities in shoulder X-rays. The ResNet18-based architecture demonstrates an average accuracy rate of 76%, with precision, recall, and F1-score equal to 75% and 74%, respectively.

The superior performance of the suggested model is due to the application of residual learning. Moreover, the convolution layers are capable of maintaining spatial correlations between pixels, and as a result, the model can detect various structures including bone fractures, joint dislocations, and bone abnormalities.

In terms of trade-off between speed and efficiency, the proposed model outperforms the competing models. For example, while achieving an accuracy of about 72%, the VGG16 model had more parameters, making it computationally intensive. In addition, the accuracy of MobileNetV2 was slightly higher than that of ResNet18 but was lower in computational efficiency, reaching 74%.

Further investigations were conducted on more complex models including ResNet50; however, it also had a high computational cost since it achieved an accuracy rate of around 78%. Moreover, although being efficient to some extent, the accuracy of the EfficientNet-based models reached similar results as that of ResNet.

The incorporation of dropout technique in the fully-connected layer of the proposed model can be seen to help overcome the problem of overfitting in order to improve generalization. Moreover, some preprocessing steps like resizing and normalization of images aid to obtain stable training.

Furthermore, it can be seen that increase in the number of images results in better performance as the network can learn more representative features. Although the proposed model performs well overall, there are still some false negatives reported, and this becomes a major problem especially in cases where there are potential life-threatening diseases, since any delay in diagnosing them will have severe consequences.

While traditional methods require taking into consideration the patient's history along with other modalities, the proposed system works based only on radiographic images.

In conclusion, the proposed system performs reliably in detecting shoulder abnormalities and significantly outperforms the chosen baseline models.

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