RESEARCH PAPER

Computer-Aided Tear Film Breakup Time Test based Dry Eye Diagnosis using Explainable AI

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Abstract: Early identification of eye disorders is important for preventing long term complications and maintaining visual comfort. Dry Eye Disease (DED) is a common ocular condition that can significantly affect the quality of life if it is not diagnosed and managed at an early stage. Among the clinical examinations used for DED assessment, the Tear Breakup Time (TBUT) test is widely used to evaluate the stability of the tear film. Motivated by the need for reliable and automated diagnostic support, this study proposes a deep learning based approach for the classification of TBUT images. A dataset of TBUT test images was collected for this study. Since the dataset is of small amount, data augmentation techniques were applied to increase the diversity of training samples and improve model performance. Prior to model training, several preprocessing steps were performed to enhance the quality of the images. Four pretrained convolutional neural network models-EfficientNetV2S, MobileNetV3, EfficientNetV2M, and ResNetV2 were employed for the classification task. In addition, Explainable Artificial Intelligence(XAI) techniques, namely Gradient-weighted Class Activation Mapping (Grad-CAM) and Local Interpretable Model-agnostic Explanations (LIME), were used to visualize and interpret the decision making process of the models. The inclusion of explainability helps improve transparency and supports the potential use of such systems in clinical environments. Experimental results indicate that EfficientNetV2S achieved the best performance among the evaluated models with accuracy of 95%. Overall, the findings demonstrate the potential of deep learning combined with XAI techniques for assisting clinicians in the diagnosis of DED using TBUT images.

Keywords: Tear film breakup time, Dry eye disease detection, Explainable Artificial Intelligence (XAI),Visual explanation of CNN, Grad-CAM, LIME, Medical image analysis, Ophthalmic image analysis

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1. Introduction

DED is a common ocular condition that occurs when the tear film becomes unstable or insufficient to maintain proper lubrication of the eye. This instability can lead to symptoms such as irritation, redness, blurred vision, and a feeling of dryness or discomfort[1-3]. One of the widely used clinical methods for assessing tear film stability is the TBUT test, where a break up pattern appearance time of less than 5 seconds indicates the presence of dry eye. According to global health reports, millions of people are affected by DED, with a higher prevalence observed among women and older adults due to hormonal and environmental factors[4-7]. Figure 1 show illustrates the clinical workflow of the TBUT test, starting with eye examination followed by instillation of fluorescein dye drops.

Finally, the tear film stability is assessed by measuring the time taken for breakup after a blink, which helps in diagnosing DED.

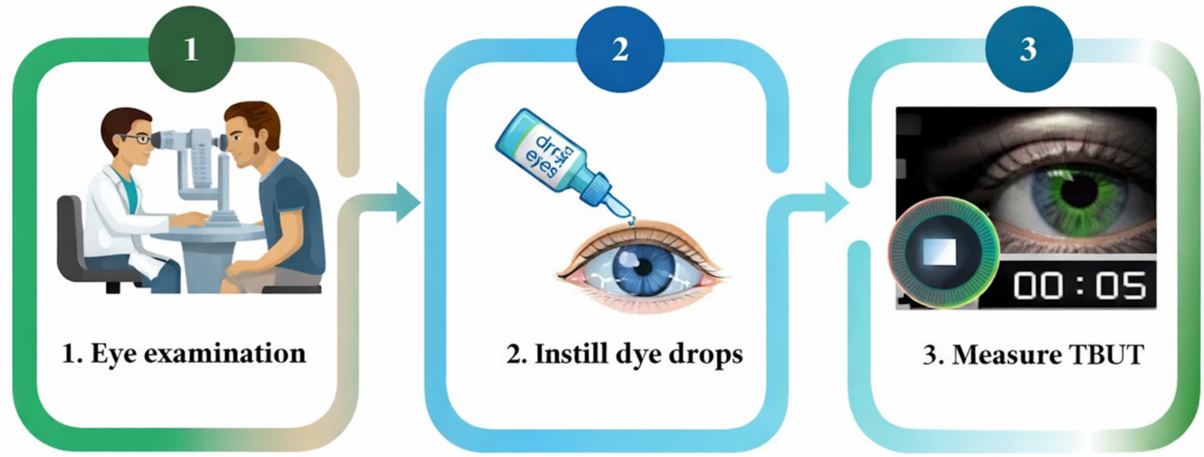

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Figure. 1. Steps for TBUT Measurement

TBUT test is most common test used in clinics but it is repetitive, time consuming and subjective in nature[7-8]. Hence to bring objectivity and reliability to the test a computer aided method is required. This study presents a deep learning based approach for the classification of TBUT images with a focus on both accuracy and interpretability. The dataset was carefully prepared, and preprocessing along with augmentation techniques were applied to improve model performance. Multiple pre-trained CNN models were evaluated and to improve transparency, explainable AI techniques were integrated into the system. These methods provided visual insights into the regions influencing model predictions, making the results easier to interpret and more suitable for clinical use.

Although DED is not life threatening like cancer, its early detection is still very important, as untreated cases can significantly impact daily activities and overall quality of life. Traditional diagnosis relies heavily on clinical expertise and manual observation, which may sometimes lead to variability in interpretation. In recent years, computer vision and deep learning techniques have shown strong potential in medical image analysis by enabling automated and consistent evaluation of large volumes of clinical data, including TBUT images. These approaches are especially useful in settings where access to experienced ophthalmologists may be limited, helping in early screening, reducing diagnostic time, and improving patient care[16-21].

Most existing studies in this area primarily focus on improving classification accuracy using deep learning models, often overlooking the importance of understanding how these models make decisions[22-28]. In contrast, this study emphasizes not only accurate classification of DED but also the interpretability of the model predictions. To achieve this, we integrate XAI techniques with advanced deep learning methods. This combination allows us to gain deeper insights into the model's decision making process and increases trust in automated diagnosis[29-33].

Deep learning, particularly Convolutional Neural networks (CNNs), has become widely adopted in medical imaging due to its ability to automatically learn complex patterns from raw data. In this work, we propose a pipeline for the classification of TBUT images to identify DED. The approach involves the use of four pre-trained CNN models, EfficientNetV2S, MobileNetV3, EfficientNetV2M, and ResNetV2 along with two explainable AI techniques, Grad-CAM and LIME. This integrated framework not only aims to achieve reliable classification performance but also provides visual explanations to support clinical understanding.

The main contributions of this work are summarized as follows:

• A detailed comparative analysis of four widely used pre-trained CNN models for TBUT based classification for DED diagnosis.

• Integration of XAI methods, including Grad CAM and LIME, to improve model transparency and interpretability.

• Evaluation of model performance using standard metrics such as Accuracy, F1-score, Recall, and Precision to ensure a comprehensive assessment.

2. Related Work

Research focused on TBUT is limited, and the key studies can be briefly outlined as follows: Qian et al[22] proposes a deep learning based system to assess tear film stability and classify tear breakup patterns like line, spot, dimple, random for DED diagnosis. Using video data and models like Mask R-CNN and temporal networks, it achieves high accuracy of 91.8% for breakup detection and 98% for dry eye identification. The approach provides an objective, non-invasive diagnostic tool that reduces human variability and supports personalized treatment of DED. Barche[23] proposes an automated system to measure tear TBUT from slit-lamp video data, reducing the subjectivity of manual clinical assessment. The model is trained and validated on clinical video datasets to accurately detect the first tear film breakup, enabling reliable and repeatable dry eye diagnosis. Overall, the approach improves diagnostic consistency and efficiency, offering an objective, A driven alternative for DED evaluation in clinical practice. Vyas[24] proposes a fine tuned MobileNetV2 network to classify tear film breakup time TBUT images for detecting DED. It focuses on improving classification accuracy while keeping the model efficient and suitable for real-time or low resource clinical settings. The results demonstrate enhanced performance compared to traditional methods, enabling faster and more reliable dry eye diagnosis. Vyas[25] presents a CNN based approach to automatically detect DED using tear film breakup time (TBUT) image data. The model learns spatial features from ocular surface images to distinguish between normal and dry eye conditions with improved accuracy. This method offers an objective and efficient alternative to manual TBUT assessment, supporting early and reliable diagnosis. Shimizu[26] develops a system to automatically estimate TBUT from ocular surface images/videos for dry eye diagnosis. It uses deep learning models to detect tear film instability patterns and quantify TBUT with high accuracy. The approach provides a non-invasive, objective, and reliable tool that enhances clinical decision making and reduces observer variability. Cebreiro[27] presents an automated system for measuring TBUT using image processing techniques applied to ocular surface videos. It detects tear film instability by analyzing intensity changes and breakup patterns, reducing dependence on manual observation. The proposed method improves objectivity, repeatability, and accuracy in dry eye diagnosis compared to traditional clinical TBUT tests. Yedidya[28] proposes an automated system for detecting DED using image processing and machine learning techniques on ocular surface data. It extracts

relevant features related to tear film quality and eye surface characteristics to classify normal and dry eye conditions. The approach enhances diagnostic accuracy and reduces manual effort, providing a faster and more objective screening method.
While many existing studies have improved the accuracy of dry eye detection using deep learning, most of these models still work like black boxes, where the decision making process is not clear to clinicians. This lack of transparency can make it difficult to fully trust the results in a medical setting. To overcome this, our work introduces an XAI approach that helps visualize and understand how the model makes its predictions. By providing clear and meaningful explanations along with accurate results, our approach improves both trust and usability, making it a novel and important contribution to DED diagnosis.

3. Background Study

A. Pre-trained CNN Models

1. **EfficientNetV2S[30]:** EfficientNetV2S is a lightweight and fast variant within the EfficientNetV2 family, designed to deliver strong performance with lower computational requirements. Similar to its larger counterpart, it uses a combination of fused and depthwise separable convolutions. The early layers focus on efficient feature extraction, while later layers are optimized for reduced computation. The model also adopts progressive learning to enhance both training speed and accuracy. Due to its compact design, EfficientNetV2S is well suited for real time applications and deployment on devices with limited resources.
2. **MobileNetV3[29]:** MobileNetV3 is specifically designed for mobile and edge devices, where computational efficiency is critical. It builds upon earlier versions of MobileNet by incorporating lightweight depthwise separable convolutions along with advanced techniques such as squeeze and excitation modules and optimized activation functions. The architecture is carefully tuned to reduce latency while maintaining good accuracy. Its compact size and efficient design make it highly suitable for applications that require fast inference with limited hardware capabilities.
3. **EfficientNetV2M[30]:** EfficientNetV2M is a moderately large convolutional neural network that aims to strike a balance between model performance and computational efficiency. The architecture combines fused convolutions in the initial layers with depthwise separable convolutions in the deeper layers. This design helps in capturing low level features efficiently at the beginning while reducing computational cost in later stages. The model also follows a progressive learning strategy, where both input image size and regularization are gradually increased during training. Compared to smaller variants, EfficientNetV2M has a deeper structure and a higher number of parameters, allowing it to learn more complex representations.
4. **ResNetV2[31]:** ResNetV2 is an improved version of the original ResNet architecture, known for its use of residual connections that help in training very deep neural networks. These skip connections allow information to flow more easily across layers, reducing issues such as vanishing gradients. In ResNetV2, the order of operations within residual blocks is modified to improve training stability and performance. This model is capable of learning complex and high level features, making it effective for a wide range of image classification tasks.

B. Explainable AI

In medical image analysis, it is important not only to achieve high accuracy but also to understand how a model makes its decisions. This is especially relevant for DED detection using TBUT images, where interpretability can support clinical trust. In this work, two explainable AI techniques, Grad-CAM and LIME are used to interpret the predictions of the trained CNN models.
Grad-CAM generates heatmaps that highlight the regions of a TBUT image most influential in the model's decision. This helps in identifying whether the model is focusing on meaningful tear film patterns during classification.
LIME explains individual predictions by approximating the model locally with a simpler interpretable model. By analyzing how small changes in the input affect the output, it identifies the regions that contribute most to the prediction.
Together, these methods improve transparency and make the model's decisions easier to understand in a clinical context.

C. Performance Metrics

To evaluate the performance of the proposed model for TBUT based Dry Eye Disease (DED) classification, standard evaluation metrics such as Accuracy, Precision, Recall, and F1-score are used. These metrics provide a comprehensive understanding of the model's effectiveness in distinguishing between normal and breakup frames.
Accuracy measures the overall correctness of the model and is defined as the ratio of correctly classified images (both normal and breakup) to the total number of images.

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP+TN+FP+FN}}$$

Precision indicates how many of the frames predicted as breakup are actually correct. It reflects the reliability of positive predictions.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$$

Recall measures the ability of the model to correctly identify all actual breakup frames. It shows how effectively the model detects tear film breakup.

$$Recall = \frac{TP}{TP+FN}$$

F1-score provides a balance between Precision and Recall and is calculated as:

$$F1\text{-}score = \frac{2 \times (\mathrm{Precision} \times \mathrm{Recall})}{(\mathrm{Precision} + \mathrm{Recall})}$$

Where, TP (True Positive) is correctly classified breakup frames, TN (True Negative) is correctly classified normal frames, FP (False Positive) is Normal frames incorrectly classified as breakup, FN (False

Negative) is Breakup frames incorrectly classified as normal

These metrics together ensure a reliable evaluation of the model's performance for TBUT-based DED detection.

4. Dataset

A well organized and reliable dataset plays a key role in developing effective model for DED detection using TBUT image classification. The performance of deep learning models largely depends on the quality and quantity of the data used for training. However, existing studies reveal that there is a limited availability of publicly accessible TBUT image datasets.

To address this gap, a dataset consisting of 150 TBUT videos was collected using two types of slit-lamp biomicroscopes, namely TOPCON and ZEISS, at Vaikunth Eye Clinic, Ahmedabad, Gujarat, India. The videos were carefully annotated frame by frame by two experienced ophthalmologists. To ensure the reliability of the ground truth, only those frames where both experts fully agreed were included in the final dataset. All videos were captured with 8 bit color depth and a resolution of 900 × 900 pixels. The dataset includes two categories of frames:

- **Normal Frame:** These frames show a stable and uniform tear film without any visible irregularities or black spots.
- **Breakup Frame:** These frames indicate tear film instability, where dark spots begin to appear, representing tear film breakup.

5. Proposed Methodology

This section describes the methodology used for DED detection using TBUT images. The overall workflow of the proposed method is illustrated in Figure 2. The proposed flow begins with TBUT video input, followed by preprocessing steps such as resizing, scaling and augmentation. The processed frames are then passed through pre-trained CNN models to classify normal and breakup. The first frame in which breakup is detected is used to calculate TBUT (for example, if breakup occurs at frame 4, TBUT = 4 seconds), which helps in identifying DED. Finally, XAI techniques such as Grad-CAM and LIME are applied to highlight important regions and provide better interpretation of the model's decisions.

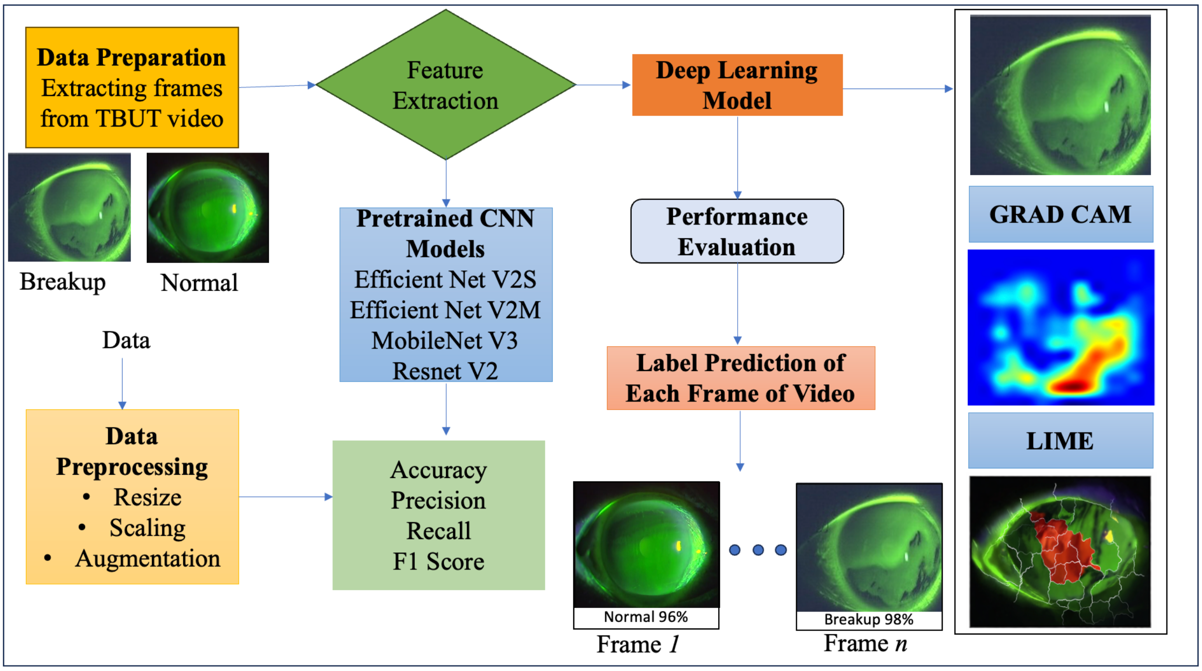


Figure. 2. Proposed Methodology for DED Detection using XAI

A. Data Preparation

The first step in the methodology is data preparation. The collected TBUT frames were initially preprocessed to improve their quality and make them suitable for model training. Since the images were of different sizes, all frames were resized to 224 × 224 pixels for uniformity. The images and corresponding labels were then converted into NumPy arrays for further processing. To improve the robustness of the model and handle the limited dataset size, data augmentation techniques were applied. These included operations such as rotation, flipping, zooming, shearing, and shifting in both width and height. These transformations help the model generalize better by exposing it to different variations of the same data. After preprocessing and augmentation, the dataset was divided into training, validation, and testing sets in the ratio of 80:10:10. Splitting was used to ensure that the distribution of normal and breakup frames remained balanced across all sets. In addition to model training, explainability is incorporated using Grad-CAM and LIME. This technique helps visualize the regions of TBUT images that influence the model's predictions, making the overall system more transparent and clinically meaningful.

TABLE I: Data distribution for each class

Class	Train	Validation	Test
Normal	2000	250	250
Breakup	2000	250	250

B. Model Training and Hyperparameter Settings

In this study, four pre-trained modelsEfficientNetV2S, EfficientNetV2M, MobileNetV3, and ResNetV2 are used for the classification of TBUT images. Each model is trained for 50 epochs with a batch size of 8. The learning rate is set to 0.001, and a dropout rate of 0.5 is used to reduce overfitting. The Adam optimizer is selected as it provides stable and efficient training performance. The main objective of this step is to enable the models to learn important patterns from TBUT images, especially subtle changes in tear film that indicate normal and breakup conditions.

To improve training, an Early Stopping callback is used, which halts training when validation performance stops improving to prevent overfitting. This helps the model achieve better convergence. In addition, a Model Checkpoint callback is applied to save the best performing model based on validation accuracy during training. For model architecture, GlobalAveragePooling2D is used after the base model to reduce the feature maps. This is followed by a Dense layer with 64 units and ReLU activation to learn more meaningful features. A dropout layer with a rate of 0.5 is added to prevent overfitting. Finally, a Dense layer with softmax activation is used to produce the output for classification. Overall, this setup ensures effective learning while maintaining model stability and generalization.

C. Model Evaluation and Explainable AI

In the final step, the performance of all the trained models is evaluated to classify TBUT images for DED detection. The comparison is carried out using standard performance metrics such as accuracy, precision, recall, and F1-score. This helps in identifying the model that performs best overall and gives the most reliable results. After evaluation, explainable AI techniques are applied to better understand how the models make their predictions. In this work, Grad-CAM and LIME are used to highlight the important regions in TBUT images that influence the classification. These methods provide visual explanations, showing whether the model is focusing on meaningful tear film patterns such as breakup areas. This combined approach not only helps in selecting the most effective model but also improves transparency by giving clear insights into the decision-making process, making the system more suitable for clinical use.

6. EXPERIMENTAL RESULT

Table 3 and Figure. 4. shows that EfficientNetV2S achieved the best performance among all the models. It obtained the highest values across all evaluation metrics, with accuracy of 0.95, recall of 0.96, precision of 0.93, and F1-score of 0.92. This clearly indicates that the model is able to classify TBUT images more accurately and consistently for both normal and breakup frames.

Table.3. Performance of pretrained models

Models	Accuracy	Precision	Recall	F1 Score
EfficientNetV2S	**0.95**	**0.93**	**0.96**	**0.92**
MobileNetV3	0.91	0.92	0.90	0.91
EfficientNetV2M	0.89	0.91	0.87	0.88
ResNetV2	0.82	0.90	0.83	0.89

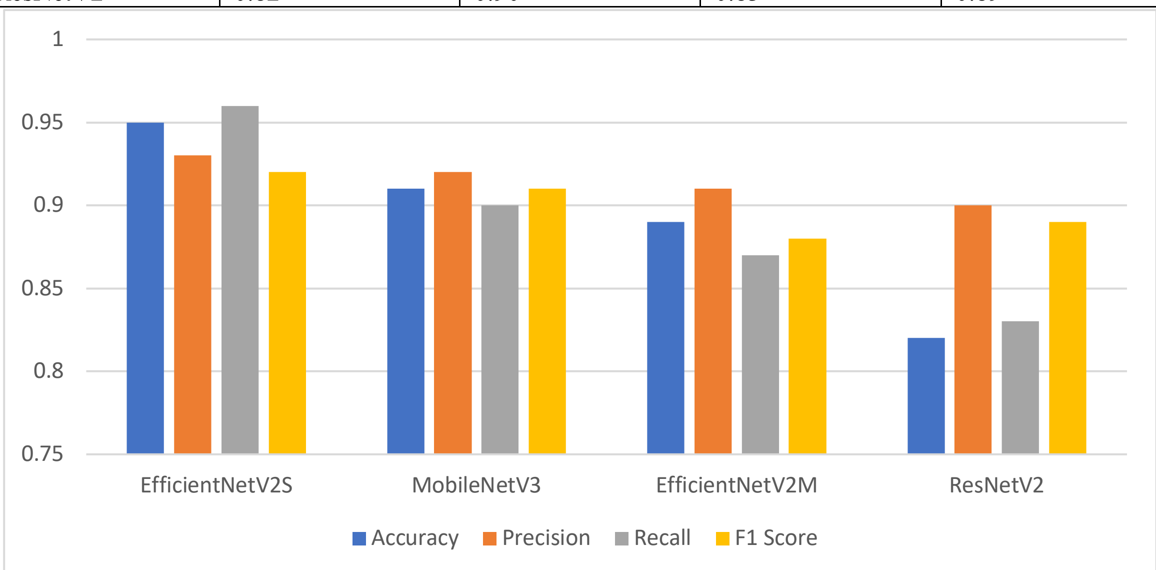


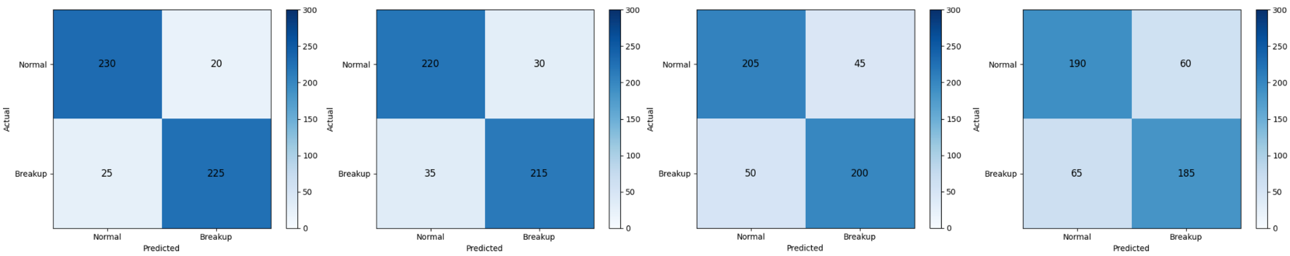
Figure. 4. Graphical representation of performance of the models

The next best performance was observed with MobileNetV3, which also showed stable and reliable results with an accuracy of 0.91 although slightly lower than EfficientNetV2S. On the other hand, EfficientNetV2M and ResNetV2 showed comparatively lower performance, with accuracies of 0.89 and 0.82, respectively. This suggests that these models were less effective in capturing important tear film features from TBUT images. Overall, EfficientNetV2S stands out as the most robust model for this classification task due to its balanced precision and recall, leading to a better F1-score.

From Figure. 5., EfficientNetV2S achieved the highest number of correct predictions by classifying 225 out of 250 test images correctly. In contrast, ResNetV2 showed the lowest performance with only 185 correct classifications. MobileNetV3 and EfficientNetV2M showed moderate results, correctly classifying 215 and 200 images, respectively. The ROC AUC analysis in Figure. 6. further confirms the effectiveness of EfficientNetV2S, which achieved high AUC values across different classes. MobileNetV3and also performed well, while EfficientNetV2M and XceptionNet slightly lower AUC scores, indicating their limited ability to distinguish between normal and breakup frames.

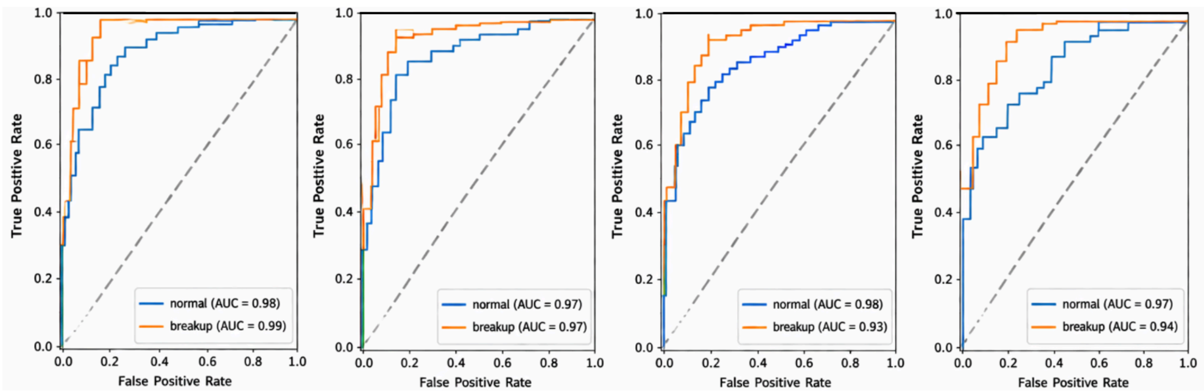
To better understand the model decisions, explainable AI techniques such as Grad-CAM and LIME were applied. Grad-CAM provided heatmaps that highlighted the important regions in TBUT images used for predictions as shown in Figure. 7. Red and yellow areas indicate high and moderate attention, mainly over tear film breakup regions, while blue areas represent less important regions. EfficientNetV2S shows more focused and accurate attention compared to other models, indicating better feature learning. LIME visualizations, shown in Figure. 8, further helped in identifying the specific areas in the images that influenced the model's predictions. Green areas indicate positive contributions supporting the prediction, while red areas show regions that negatively impact the decision. EfficientNetV2S highlights more relevant and focused breakup regions, whereas other models show comparatively scattered or less precise attention.

Figure. 9. shows final result interpretation proposed TBUT workflow showing from the input video, frame extraction is done at 1 frame per second, whenever the first breakup is detected, that is considered as breakup time, as shown in figure. 9. The breakup is detected at frame 3, resulting in a TBUT value of 3 seconds.



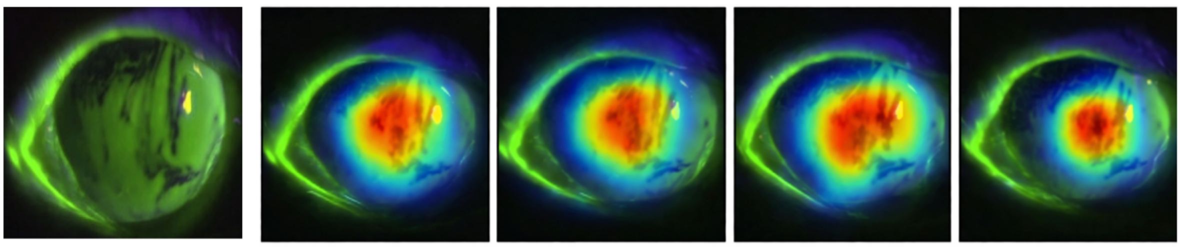
a) EfficientNetV2S b) MobileNetV3 c) EfficientNetV2M d) ResNetV2

Figure. 5. Confusion matrix of pretrained network



a) EfficientNetV2S b) MobileNetV3 c) EfficientNetV2M d) ResNetV2

Figure. 6. ROC Curve pretrained network



Input Image a) EfficientNetV2S b) MobileNetV3 c) EfficientNetV2M d) ResNetV2

Figure.7. Visualization using Grad-CAM for model predictions

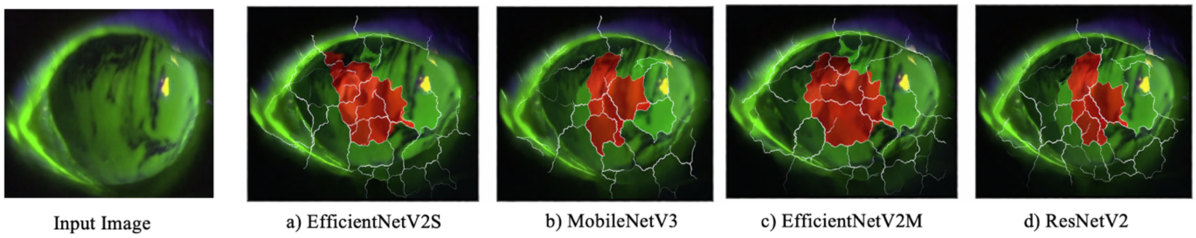


Figure. 8. Visualization using LIME for model predictions

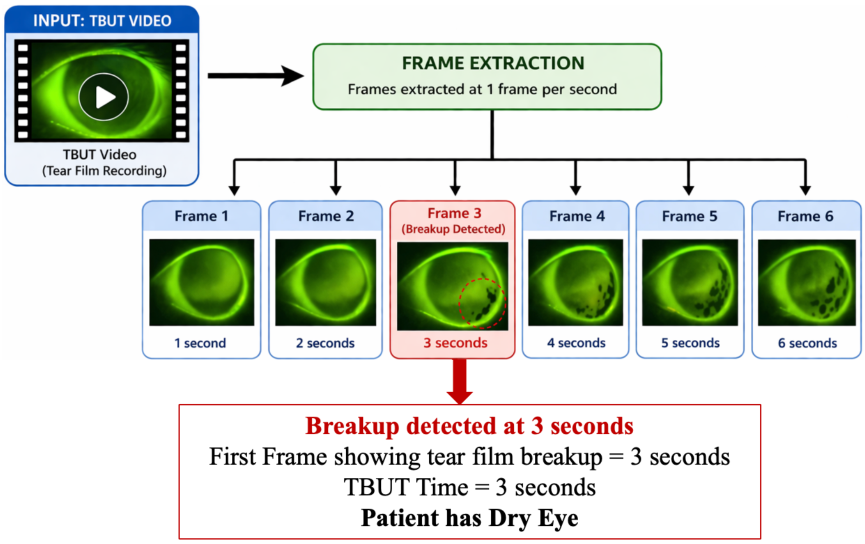


Figure. 9. Final result interpretation of the proposed TBUT analysis

7. Conclusion

This study presents a deep learning based approach for the classification of TBUT images for DED detection, with a focus accuracy and interpretability. The dataset is prepared, and preprocessing of images along with augmentation techniques were applied to improve the performance of model. Different pretrained CNN models were evaluated, and EfficientNetV2S showed the best results in terms of accuracy, precision, recall, and F1-score. This indicates its strong ability to capture subtle tear film breakup and accurately distinguish between normal and breakup frames. To improve transparency, explainable AI techniques such as Grad-CAM and LIME were integrated into the system. These methods provided visual insights into the regions influencing model predictions, making the results easier to interpret and more suitable for clinical use. Although the availability of large scale TBUT datasets remains a limitation, the proposed approach demonstrates promising performance. In future work, the use of larger datasets, advanced architectures, and improved preprocessing methods can further enhance the system. Overall, this work highlights the potential of combining deep learning and explainable AI for reliable and interpretable DED detection.

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