

# Clinically-Validated Innovative Mobile Application for Assessing Blinking and Eyelid Movements

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**Abstract.** Blinking is a vital physiological process that protects and maintains the health of the ocular surface. Objective assessment of eyelid movements remains challenging due to the complexity, cost, and limited clinical applicability of existing tools. This study presents the clinical validation of Bapp (Blink Application), a mobile application developed using the Flutter framework and integrated with Google ML Kit for on-device, real-time analysis of eyelid movements. The validation occurred using 45 videos from real patients, whose blinks were manually annotated by ophthalmology specialists from the Paulista School of Medicine of the Federal University of São Paulo (EPM-UNIFESP) to serve as the ground truth. Bapp's performance was evaluated using standard metrics, including Precision, Recall, and F1-Score, with results demonstrating 98.4% precision, 96.9% recall, and an overall accuracy of 98.3%. These outcomes confirm the reliability of Bapp as a portable, accessible, and objective tool for monitoring both normal and abnormal eyelid movements. The application offers a promising alternative to traditional manual blink counting, supporting continuous ocular health monitoring and postoperative evaluation in clinical environments.

**Keywords:** Eyelid Movement; Blink Detection; Mobile Application; Artificial Intelligence; Clinical Validation;

## 1 Introduction

Eye blinking is a rapid movement involving the closing and reopening of the eyelids, playing a crucial role in protecting eye health and supporting visual processing [1]. Spontaneous blinking is an involuntary, brief eyelid closure that helps preserve ocular surface health and maintain visual clarity by evenly spreading the tear film [2].

Effective eyelid blinking is essential for maintaining visual function, distributing the tear film across the eye surface, and ensuring adequate tear drainage. Changes in blinking may occur in conditions such as dry eye syndrome or eyelid ptosis, or after eyelid surgery, and can potentially harm eye health. Conditions such as dry eye syndrome, eyelid ptosis, or those following eyelid surgeries, can potentially compromise ocular health [2–4].

Analyzing eyelid blinking and movement is crucial for monitoring patients with abnormal eyelid behavior. This analysis involves capturing facial images and using specialized software to objectively recognize and measure eyelid movements [5–8]. Unfortunately, such approaches often involve complex systems that are impractical for clinical settings. Additionally, they tend to be imprecise, especially for patients with abnormal eyelid movements, and fail to capture other critical parameters, such as amplitude movements [5–8].

Image acquisition occurs by using external cameras or the built-in cameras of mobile devices [5–8]. The captured images are then analyzed using computational tools such as MATLAB to detect and measure eyelid movements [6]. Alternatively, the user can rely on web-based platforms accessible via mobile devices or desktop computers to conduct these studies [5].

This work aims to validate a mobile application designed to assess eyelid movement by recording eye opening and closing over time. The validation occurs by comparing its performance against a ground truth established through frame-by-frame annotations from EPM-UNIFESP ophthalmology specialists on a sample of real patient videos. The application utilizes machine learning and computer vision tools. It offers a reliable framework for analyzing the frequency and amplitude of both normal and abnormal eyelid movements, providing a scalable and accessible solution for clinical and research use.

## 2 Related Works

Technological advancements have enhanced the analysis of eyelid blinking and movement, particularly in patient monitoring settings where more resources are available. Techniques such as high-speed imaging, deep learning, and smartphone-collected videos now offer portable, accurate, and non-invasive methods for evaluating blink behavior and its connection to various eye conditions.

High-speed imaging captures rapid movements at very high frame rates, enabling precise slow-motion visualization and detailed analysis of fast-moving dynamic events. When combined with digital image correlation (DIC), high-speed imaging allows accurate measurement of eyelid motion during blinking. This method captures detailed kinematic data—such as blink duration, eyelid displacement, and peak velocity—allowing a thorough assessment of both spontaneous and reflex blinks [9].

Intelligent vision measurement systems that use deep learning can analyze eye openness and provide insights into patients' visual function, especially those with dry eye disease. These systems provide information for assessing blink completeness and deliver consistent, precise measurements, improving clinical evaluations [10, 11].

Using smartphones to capture videos has proven effective for collecting raw data on eyelid movements, enabling comparative analysis of blink dynamics in patients. This approach is cost-effective and accessible, making it suitable for both clinical and research uses [12], as well as for initial self-assessment.

Few mobile applications currently provide an objective analysis of eyelid movements. Among them, DryEyeRhythm and EyeScore were developed to assess blink patterns for dry eye diagnosis; however, the latter remains unavailable for download [13, 14]. There is no comparative validation using these apps against public datasets and clinical data.

A different method for analyzing blinks in videos involves running the application on a cloud server. The patient videos are recorded locally with a camera or smartphone and then uploaded to a web server for processing and analysis of eyelid movement. One project that adopted this method employed the Streamlit platform to host the app [5].

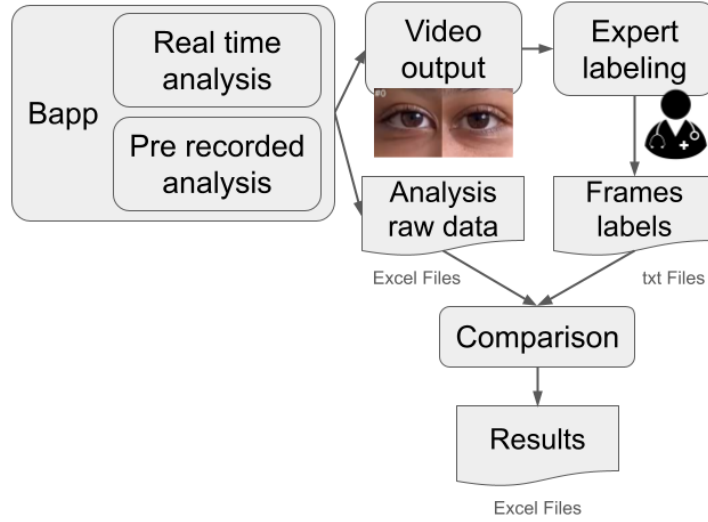
Although these technological advancements offer substantial benefits for tracking eyelid movement, challenges persist in standardizing these techniques across various clinical environments and promoting their widespread adoption. Additional research is necessary to confirm the effectiveness and reliability of these technologies across different patient groups, including individuals of diverse ethnicities and age ranges.

### 3 Proposed Method

For clarity, **Fig. 1** illustrates the steps and tools used in the proposed method. To clinically validate the mobile application Bapp (Blink Application), we utilized annotated videos from analyses conducted by specialists from EPM-UNIFESP, which indicate the locations where blinks occur. When a study is conducted using Bapp, an output video is generated that displays only the eye region, allowing specialists to validate the results against Bapp's findings after analysis. This video is generated from both real-time analysis and pre-recorded video analysis. The EPM-UNIFESP specialist analyses this video frame by frame and annotates the blinks in a text file, specifying the start and end frames for each blink.

Bapp can also generate an Excel file containing the raw data from the analysis, including, for each analyzed frame, the eye-openness probability and the EAR from Google ML Kit for both eyes.

The next step is to compare the blinks detected by the app algorithm with the annotated blinks by the specialists.



**Fig. 1.** Diagram showing steps and tools used to analyze eyelid movements from videos generated by Bapp analysis, and comparing the results from the Bapp mobile application to the annotated data from specialists.

### 3.1 Annotated Videos

Spontaneous blinking was recorded bilaterally using the Bapp App [15, 16]. All recordings were conducted with participants maintaining a primary gaze position under standardized conditions. Individuals with any eyelid, ocular surface, or neurological disorders that could affect blinking were excluded from the study.

The specialist from EPM-UNIFESP annotates blink occurrences in the output video created by Bapp in a text file. The footage is reviewed frame by frame manually, and the frames where the blink begins and ends are recorded, along with whether the blink is complete. When the eyelids fully close, the blink is considered complete; otherwise, it is classified as a partial blink. These annotations are the ground truth information, which will be compared with the Bapp output.

**Fig. 2** shows a sequence of frames from video #7 that illustrates a complete blink. **Table 1** has the annotated information for video #7. The first blink starts at frame #36 and ends at frame #41. **Fig. 2** depicts this range.

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**Fig. 2.** Frames from the video #7 showing a complete blink.

**Table 1.** Video #7 annotated frames showing the start and end of blinks.

Video #	Annotations
7	36-41c 117-123c 182-185i 212-217c 294-298c 384-388c 448-453c 477-480i 502-508c 581-585c 740-745c 799-803i 815-821c 869-873c 1016-1019i 1063-1066i 1151-1155c 1212-1217c 1288-1293c 1350-1354c 1427-1432c 1513-1517c 1582-1585i 1631-1635c 1730-1735c 1748-1750i

### 3.2 Blink Raw Data

The Bapp mobile application features an export function for raw eye openness probabilities and the Eye Aspect Ratio (EAR) for both eyes to an Excel file [16]. **Table 2** displays data from frames 30-45 of video #7, extracted from the Excel file produced by Bapp.

**Table 2.** Video #7 raw blink data from Excel.

Frame	Right Eye Openness	Left Eye Openness	Right Eye EAR	Left Eye EAR
30	0.992	0.999	0.326	0.326
31	0.988	0.998	0.326	0.326
32	0.992	0.998	0.326	0.326
33	0.993	0.999	0.337	0.326

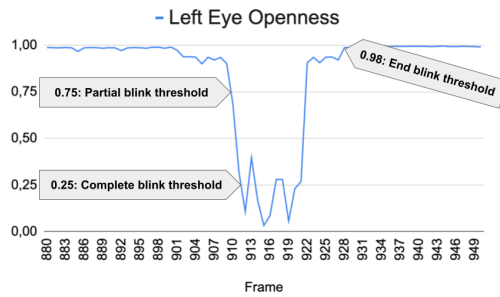
34	0.992	0.998	0.326	0.322
35	0.993	0.691	0.236	0.225
36	0.024	0.003	0.191	0.188
37	0.029	0.001	0.189	0.200
38	0.084	0.019	0.229	0.222
39	0.994	0.987	0.275	0.255
40	0.994	0.996	0.288	0.296
41	0.995	0.998	0.324	0.304
42	0.991	0.999	0.339	0.313
43	0.993	0.998	0.335	0.328
44	0.993	0.997	0.332	0.328
45	0.993	0.997	0.339	0.326

### 3.3 Eye Blink Detection Algorithm

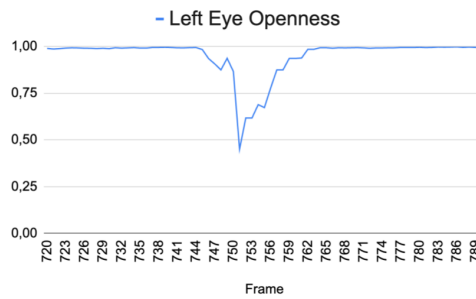
The interpretation of raw data from Google ML Kit identifies the frames in which a blink occurs. A blink begins when the eye openness probability falls below 0.75, where 0.0 represents a fully closed eye and 1.0 represents a fully open eye. If the eye openness probability drops below 0.25, the blink is classified as complete; otherwise, it is considered partial. The blink ends when the eye openness probability rises above 0.98. **Fig. 3** illustrates these thresholds.

**Fig. 4(a)** illustrates an instance of a partial blink, where the eye openness probability decreases below 0.75 but remains above the 0.25 threshold, which characterizes a complete blink. The blink is classified as complete upon the eye openness probability returning to 0.98. **Fig. 4(b)** demonstrates a complete blink when the eye openness probability drops below 0.25.

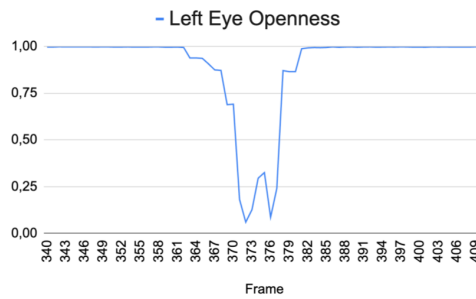
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**Fig. 3.** Illustration of probability charts with thresholds indicating the beginning and ending of partial or complete blinks.



(a)

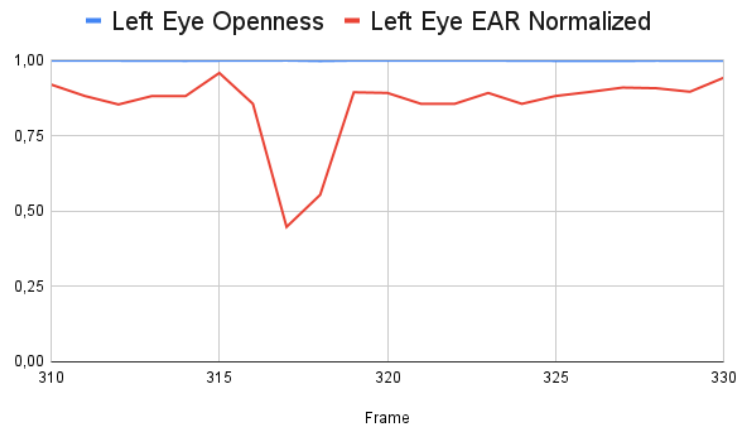


(b)

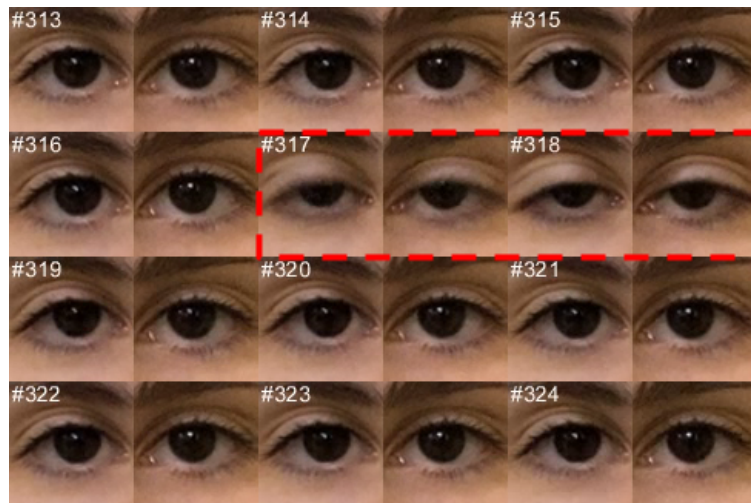
**Fig. 4.** Illustration of probability charts of partial blink (a) and complete blink (b)

Another way to detect blinks is using the EAR, which is much more sensitive to partial blinks. In the present study, we use a combination of eye openness probability, which is very effective in detecting complete blinks and EAR. **Fig. 5** illustrates a scenario where the EPM-UNIFESP specialist annotated a partial blink, but the eye openness

probability was unable to detect it; however, EAR detected it. **Fig. 6** illustrates the frame sequence corresponding to the chart shown in **Fig. 5**.



**Fig. 5.** Illustration of eye open probability and eye aspect ratio (EAR) normalized for a partial blink scenario.



**Fig. 6.** Frame sequence for a partial blink scenario.



### 3.4 Validation

For each analysis, the raw data exported from Bapp using the Export to Excel feature will be compared with the annotations provided by EPM-UNIFESP specialists. A Python script will perform this validation by comparing the frame ranges in which blinks are detected by Bapp with those identified by the EPM-UNIFESP specialists.

To perform the statistics calculations, the following information is generated:

- True Positive (TP): When Bapp detects a blink and the annotations have an overlapping blink in the same frame range.
- False Positive (FP): When Bapp detects a blink, and the annotations don't have an overlapping blink in the same frame range.
- False Negative (FN): When an annotated blink frame range doesn't have an overlapping blink detected by Bapp.
- True Negative (TN): When an open eyes range is detected by Bapp and no blink is annotated by the EPM-UNIFESP specialists.

Fig. 7 shows a confusion matrix.

**Confusion Matrix**

<b>Actual Label</b>	Actual Negative	<b>True Negatives</b>	<b>False Positives</b>
	Actual Positive	<b>False Negatives</b>	<b>True Positives</b>
		Predicted Negative	Predicted Positive
		<b>Predicted Label</b>	

**Fig. 7.** Confusion matrix.

To calculate statistics from the confusion matrix data, we used the following equations:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall(TP \text{ rate}) = \frac{TP}{TP+FN} \quad (2)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Precision represents the proportion of correct detections among all detected events. It is crucial when the cost of a false positive—detecting a blink that did not actually occur—is high. In this context, a high precision value indicates that the system produces very few false detections, ensuring that most identified blinks are genuine.

Recall measures the system’s ability to detect all actual events, in this case, genuine blinks. A high recall indicates that the model successfully identifies most of the actual blinks, thereby minimizing the number of missed detections. This metric is especially relevant when it is critical not to overlook any blink occurrences.

F1-Score combines precision and recall into a single balanced measure. It provides a more comprehensive assessment of the system’s performance, especially when there is a trade-off between maximizing the number of blinks detected (high recall) and ensuring that detections are accurate (high precision).

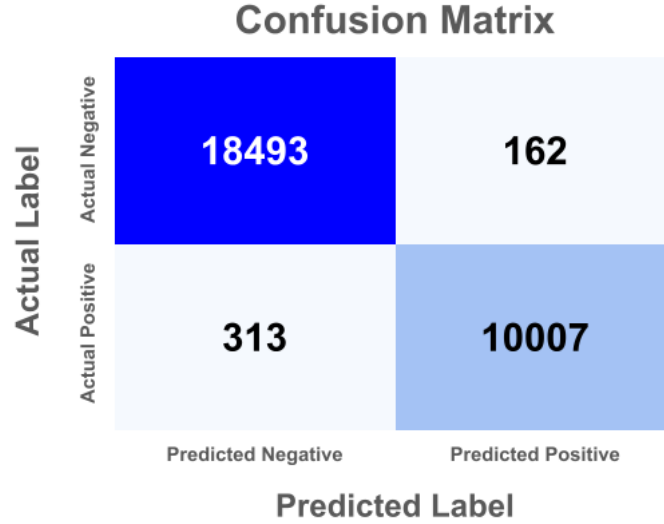
Accuracy reflects the overall proportion of correct classifications, including both blinks and non-blinks. Although this value is high, accuracy alone can be misleading in cases where the data are imbalanced—for example, when there are many more non-blink frames than blink frames. Therefore, while useful as a general indicator, it should be interpreted in conjunction with the other metrics.

## 4 Results

We used 45 raw analysis datasets from 28 different individuals. The EPM-UNIFESP specialists annotated these 45 videos generated by the analysis, totaling 28,975 individual frames. The confusion matrix produced by the analysis is shown in **Fig. 8**.

The metrics are:

- Accuracy: 0.9836
- Precision: 0.9841
- Recall (Sensitivity/True Positive Rate): 0.9697
- F1-Score: 0.9768



**Fig. 8.** Confusion matrix using the complementary EAR algorithm.

## 5 Discussion

This work presents the results of Bapp, a mobile application with machine-learning capabilities that analyzes eyelid movements in pre-recorded videos and in real-time analysis. Enhanced with the EAR algorithm, it achieved a precision of 98.4% in blink detection using data from 45 raw analyses. The precision level achieved by Bapp in its previous analysis using public datasets was 95.3% for the Talking Face and 84.3% for the EyeBlink8 dataset [16].

These precision levels enable Bapp to analyze eyelid movements instead of relying on manual blink counting, which primarily helps in monitoring abnormal eyelid activity.

Using videos with annotations provided by EPM-UNIFESP specialists in clinical settings enables validation with a more diverse dataset. It helps address the shortage of datasets annotated by field experts.

This study has some limitations. A primary limitation is the length of the analytical process, which depends on multiple factors, including the resolution of the recorded video and the computational power of the device used. Higher video resolutions require longer processing times, while devices with faster processors can complete the analysis more quickly. However, such devices are generally more expensive than those with slower processors, which take more time to perform the same tasks.

Another important limitation affecting the quality of the analysis relates to lighting conditions and camera positioning during image capture. Best results are achieved with proper lighting, with the subject facing directly toward the camera in a frontal position.

Camera stability is also crucial. The setup should include a suitable mounting system to reduce camera movement, as any instability can decrease image quality and negatively impact the accuracy of the analysis.

Future developments of Bapp may include the integration of deep learning models to enhance the detection of subtle eyelid movements and improve the classification of partial blinks. The application could also be adapted for telemedicine platforms, allowing remote and continuous monitoring of patients with ocular surface disorders, facial nerve palsy, or postoperative conditions. Moreover, its portability and real-time analysis capabilities make it suitable for longitudinal studies on blink dynamics and treatment response, such as evaluating the effects of botulinum toxin or assessing dry eye therapy outcomes. Expanding validation to larger and more diverse populations will be essential to confirm the model's robustness and ensure its applicability across different clinical scenarios.

## 6 Conclusion

The Bapp application successfully underwent clinical validation using expert annotations from EPM-UNIFESP specialists on real patient videos, demonstrating reliable and objective detection of eyelid movements. The system achieved a precision of 98.4% and a recall of 96.9%, confirming its high accuracy and robustness for both normal and abnormal blink detection. These results reinforce Bapp's potential as a portable, accessible, and multilingual tool for continuous patient monitoring and postoperative evaluation. Future work will focus on expanding validation to larger and more diverse populations, further establishing the clinical applicability of this approach.

## 7 Conflict of Interest

The authors declare that they have no conflict of interest.

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