

ParaTrackNet: AI-Powered Real-Time Parathyroid Gland Detection and Tracking During ICG-Assisted Thyroidectomy

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Abstract— An increase in the number of thyroid cancers have increased the number of thyroidectomies. It is very important to keep the parathyroid glands (PGs) safe as disruption to it can cause significant complications. Traditionally, the identification of the parathyroid gland is relied on visual inspection. Now, it is found that PGs show fluorescence after ICG dye is injected into the bloodstream, when stimulated with near-infrared (NIR) light. In this research paper, a proposed method called ParaTrackNet for detecting and tracking parathyroid glands during surgical procedures such as thyroidectomies is presented using fluorescence imaging with ICG, OpenCV and Kalman filtering. The parathyroid glands show a distinct green when exposed to NIR light after the ICG is injected into the bloodstream which enables the detection and differentiation from the tissues surrounding it. The approach presented here uses real-time computer vision and deep learning techniques using OpenCV, ORB feature and Kalman filtering to identify the green fluorescence and track the parathyroid glands as lighting conditions change from NIR to normal surgical lighting. The proposed ParaTrackNet demonstrates high robustness under variable lighting conditions and anatomical variations, achieving an accuracy of 96.78% and a F1-score of 97.2%, and an average processing time of 40ms per frame. The results highlight the proposed AI-powered parathyroid detection ensemble models resource efficient and practical solution with potential to support during real-time intraoperative scenarios, where consistent and accurate tracking is critical.

Keywords— Parathyroid gland, Thyroidectomy, Near-Infrared Imaging, Autofluorescence, OpenCV, CSRT Tracker, Kalman Filter, ORB Matching.

I. INTRODUCTION

Thyroidectomy procedures have increased globally as a result of an increasing prevalence of thyroid cancer. It is one of the most common endocrine surgeries performed worldwide, with an approximate of 150,000 procedures performed annually in the United States alone [1]. While being generally safe, unintended damage or removal of the parathyroid glands is a serious complication that can occur in 1–30% of cases, depending on the surgical skill and case complexity [2]. These tiny, typically 3–5 mm endocrine organs can sustain damage that causes either temporary or chronic hypoparathyroidism, which in severe cases necessitates lifelong calcium supplementation[3].

Parathyroid identification during surgical procedures is difficult for several reasons, including their small size, being visually similar to fat and lymph nodes, and anatomical diversity (ectopic placements in 15–20% of patients) [4]. Traditional methods of identification rely on visual cues and the surgeon's experience shows error rates that are as high as 30% [5]. By enhancing gland visualisation through characteristic fluorescence, Indocyanine Green (ICG) has emerged as a viable option for near-infrared fluorescence imaging [6]. However, continuous tracking is broken by switching between NIR and white light, making interpretation still subjective.

Artificial intelligence provides various opportunities to overcome these limitations. Medical image analysis has advanced significantly due to computer vision methods, particularly deep learning models [7]. If these technologies are modified for real time processing, they might be able to provide objective, automatic parathyroid identification while maintaining continuous tracking. But surgical applications require a careful balancing act between computing efficiency and accuracy.

This paper introduces a new AI-powered model for real-time parathyroid gland tracking and detection thyroidectomy procedures assisted by ICG. The methodology uses a multi stage approach that begins with fluorescence based segmentation using HSV colour space transformation to successfully separate the characteristic green fluorescence of ICG-enhanced parathyroid glands. Building on this segmentation, the system uses ORB (Orientated FAST and Rotated BRIEF) feature extraction to track and identify distinct gland features over a sequence of video frames. To provide consistent and dependable tracking performance, the system integrates an adaptive tracking architecture that combines the discriminative powers of CSRT (Channel and Spatial Reliability Tracker) with the predictive power of Kalman filtering. This hybrid approach ensures continuous tracking even in challenging situations, like brief occlusions or lighting changes between NIR and white light illumination, while maintaining detection accuracy and satisfying the demanding real-time requirements of surgical applications.

II. LITERATURE SURVEY

Precise intraoperative identification of parathyroid glands (PGs) is imperative in endocrine surgery, specifically in thyroidectomy and parathyroidectomy, where intraoperative injury or incorrect identification may lead to postoperative hypocalcemia and delayed complications. Standard identification techniques that depend solely on visual examination and surgeon expertise usually fail because of the small size, unpredictable position, and indistinguishable appearance of PGs from the adjacent tissues. To overcome this issue, artificial intelligence (AI) and computer vision methods have been proposed to facilitate real-time detection and classification of PGs based on image data acquired under near-infrared autofluorescence (NIRAF) or other imaging modalities. One of the significant contributions towards this direction is the research of Sang et al. [8], who introduced the Video-Trans-UHRNet, which is an enhanced high-resolution network with transformer that combines temporal and spatial information between video frames. Trained with a large dataset consisting of 9,421 labeled images from 139 surgical videos, the model attained a DICE coefficient of 0.760 and could localize PGs in real-time at a level of performance similar to that of senior endocrine surgeons. The study highlighted the advantage of using video-based temporal modeling and indicated the possibility of AI as a support tool for surgical decision-making. In the same vein, Wang et al. [13] created PTAIR 2.0, which was a better iteration of their previous version on the YOLOX model and tested it on a large dataset of more than 32,000 images of 324 patients. Their model recorded an average precision (AP50) of 92.1% and had strong ischemia detection accuracy, also at 92.1%, beating both junior and senior surgeons. In a clinical setting the application of the model in real time reveals the readiness of object detection architectures like YOLOX for deployment when trained on large, heterogeneous, and clinically applicable data.

To boost model accuracy further and overcome limitations like small object size as well as challenging surgical environments, a number of research studies have evaluated the performance of various deep learning architectures as well as hybrid methods. Yu et al. [10] compared various segmentation models, specifically U-Net, Mask R-CNN, and transformer-based Instance Segmentation Transformer (ISTR), on a dataset of NIRAF images. Their findings showed that ISTR had the highest precision (83.5%) and F1-score (81.4%), proving that transformer-based models that learn long-range dependencies are more appropriate for the fine visual features of PGs. Akbulut et al. [9] investigated the application of quantitative NIRAF imaging in conjunction with decision tree-based machine learning, obtaining 84% accuracy in the differentiation of adenomatous and hyperplastic parathyroid tissues. Their study demonstrates how the use of spectral information with conventional machine learning classifiers can be used to augment deep learning methods and minimize dependency on large image databases. Eun et al. [11] addressed the constraint of having limited labeled data through sophisticated data augmentation methods like inpainting with DeepFill v2 and geometric

operations like rotation and flipping. From their work, they showed that synthetically generated data through DeepFill enhanced the PG classification accuracy of the model, indicating that data augmentation is still a potent tactic when ground truth annotations are limited in medical imaging. Additionally, transfer learning remains a valuable technique for enhancing performance on small surgical datasets. When there is a shortage of labelled surgical data, models can achieve greater generalisation and faster convergence by utilising pretrained convolutional backbones or feature extractors. Future revisions of the ParaTrackNet system should investigate this area because of the potential it offers.

At the same time, Kim et al. [18] used YOLOv5 for parathyroid localization and achieved a high F1-score of 0.94, whereas Wang et al. [13] showed that Faster R-CNN provided better detection accuracy compared to SSD and YOLOv3, especially in complicated surgical areas with occlusions. All these results indicate that object detection networks with region proposal mechanisms (e.g., Faster R-CNN) are especially useful for detecting PGs under different lighting and anatomical conditions.

Beyond deep learning by itself, there have been various studies that integrated AI into advanced optical imaging modalities to enhance sensitivity and specificity for identifying PG. Marsden et al. [14] presented Fluorescence Lifetime Imaging (FLIm), a label-free method that identifies PGs according to tissue-specific fluorescence decay patterns. Through random forest classification of FLIm-derived features, they obtained 100% sensitivity and 93% specificity, noting the promise of the approach for intraoperative imaging without invasion and high contrast. Also, Wang et al. [15] employed Laser-Induced Breakdown Spectroscopy or LIBS along with artificial neural networks (ANNs) with 97% classification accuracy between PGs and the surrounding tissues. The results show the promise of spectral-based tissue classification when integrated with AI models for real-time imaging. Avci et al. [16] and Akgun et al. [17] used CNNs for the classification of normal vs. abnormal PGs based on autofluorescence imaging, allowing early detection of pathology with less hardware. Berber et al. [12] further advanced the process by combining real-time imaging with machine learning classification in a clinical workflow, showing the use of AI-aided PG localization in a real-life surgical environment. Even yet, a number of studies, including those by Sang [8] and Wang [13], highlight the need for improved workflow integration, cross-institutional verification, and larger datasets that reflect a wider variety of clinical and demographic characteristics. In general, these studies confirm that the intersection of AI, NIRAF, and optical spectroscopy can revolutionize endocrine surgery, reducing complications and improving surgical accuracy through smart intraoperative decision-making.

III. PROPOSED PARATRACKNET

The proposed **ParaTrackNet** architecture is an AI powered approach for real-time detection and tracking of parathyroid glands during ICG imaging in thyroidectomy includes several integrated modules. Each module is designed to make sure of accurate and reliable identification of PGs

during surgical operations, leveraging the distinct green fluorescence of the glands under near infrared (NIR) light.

A. Preprocessing

The preprocessing module helps in preparing the surgical video frames for analysis. The images are taken from the surgical footage where parathyroid glands exhibit fluorescence when exposed to NIR light after the ICG dye is injected into the patient's bloodstream. The RGB images are transformed to HSV (Hue, Saturation, Value) colour space in order to detect the parathyroid glands' distinctive green fluorescence. This change is crucial because HSV representation makes it simpler to isolate certain colours by separating colour information (hue) from intensity information (value).

Gaussian blur is used to the HSV images to lower the noise and improve the detection process' accuracy. This blurring smooths the image, reducing the impact of small, irrelevant details and potential noise that could otherwise lead to false positives. For identifying and matching the critical sections in the subsequent frames, ORB is used for extraction of key features from the images. These pre-processing steps ensures uniform preparation of the input images and accurate detection of PGs in further steps.

B. NIRF Imaging and Fluorescence Based Detection

This module identifies the regions in the preprocessed images which show the characteristic green fluorescence of the parathyroid glands. Color thresholding is used to achieve this, effectively masking non-parathyroid regions and isolating true gland fluorescence based on defined HSV threshold values that differentiate parathyroid tissue from background fluorescence. This process involves selecting the range of hue, saturation and value that correspond to green color emitted by parathyroid glands under NIR light.

For removing the small artefacts and refining the regions of interest, morphological operation like opening and closing using a structuring element are applied. Closing fills the small holes in the foreground and opening removes small objects from the foreground (based on structuring element). For eliminating noise and small irrelevant regions, these operations are critical and improve the accuracy of subsequent contour detection. The contours of the masked regions are then detected, representing the potential locations of parathyroid glands. For determining the location and shape of the fluorescent areas and for identifying the parathyroid glands, contour detection is crucial.

C. AI based parathyroid detection and tracking (ParaTrackNet)

This module ensures that the detected parathyroid glands are continuously monitored when lighting conditions change between normal and NIR surgical lighting. Initially, CSRT (Discriminative Correlation Filter with Channel and Spatial Reliability) tracker from OpenCV was used for monitoring the movements of the detected glands. CSRT was selected due to its robustness in handling occlusion and scale variations, making it suitable for surgical procedures. However, initial testing with CSRT alone yielded suboptimal tracking performance. The evaluation metrics for the system using only CSRT were as given in the Table 2

As observed, the model reaches an optimal precision (0.9283) but at the same time does not identify the most relevant example cases which is shown by the low recall value (0.6519). The F1-score (0.7659) reveals that there is a reasonable balance between the level of precision and recall, but there remains a deficit in the positive detections. The model reports accuracy (0.7757) but insensitivity to gland contours suggests insufficient capture of gland detection. These findings suggest the need for more active tracking to avoid missed detections while maintaining adequate precision and detection thresholds, which serves the purpose of the new model proposed in this study.

To improve tracking accuracy, a Kalman filter was integrated with CSRT, forming an ensemble model. Its predictive capability ensured robust tracking even during lighting changes or occlusions. The combined approach of NIR-based color detection, CSRT, and Kalman filtering significantly enhanced accuracy and maintained consistent bounding boxes, preventing missed detections and abrupt shifts during surgery.

D. Kalman Filtering for Robust Tracking

The Kalman filter is crucial for maintaining the parathyroid gland's tracking, especially when the gland is briefly obscured or lost as a result of shifting lighting conditions. A smoother and more dependable tracking experience is guaranteed by the predictive technology that predicts the glands' position in upcoming frames. The position and velocity of the observed gland are represented by a state vector that is used to initialise the Kalman filter. By combining location and velocity components, the transition matrix specifies how the state changes over time and enables the model to forecast the gland's movement. The uncertainties in detecting the position and in motion prediction are addressed by measurement noise covariance and process noise covariance, while the state vector is mapped to the observed position by the measurement matrix.

The coordinates of the bounding box are used to initialize the Kalman filter when the fluorescent region is identified. In each frame the expected position of the gland is predicted based on the previous state. The Kalman filter refines its estimate by updating its prediction using the identified position when the tracking system successfully detects the gland. When the gland is lost due to lighting changes in the surgical procedure, the filter will continue to predict its position, which are later confirmed by ORB feature matching when returned to normal lighting conditions. This predictive method guarantees that tracking remains steady even during temporary occlusions. By lessening bounding box variations brought on by noise or sudden motions, the Kalman filter enhances tracking performance overall. It improves the accuracy of the real-time parathyroid gland detection system by flattening the trajectory and ensuring steady tracking.

E. System Validation and Performance Analysis

The evaluation module assesses the performance of the detection and tracking system using a dataset containing surgical video footage with over 2000 frames. This private dataset was obtained from MACS Clinic, Bangalore, and is not publicly available due to patient confidentiality and institutional restrictions. The following performance measures are used to assess the system's performance: processing time per frame, bounding box area over time, and intersection over

union (IoU). The system's capacity to reliably and precisely follow the PG in a variety of lighting scenarios, occlusions, and motion dynamics can be fully understood thanks to these measures.

IoU calculates the overlap between the ground truth and the anticipated bounding box, giving information on the tracker's accuracy. A tracking accuracy and stability are indicated by a high IoU (above 0.85). With minor variations mostly due to lighting variations and transient occlusions, the results show that the system maintains consistent tracking performance for the majority of frames.. The combination of CSRT tracking, ORB feature matching, and Kalman filtering enables rapid recovery from these challenges, ensuring robust tracking.

Bounding box area over time is visualized to assess the tracking consistency. Sudden increases or decreases in the bounding box size can indicate misidentifications or tracking failures. Even when minor fluctuations occur in the results, Kalman filters predictive capabilities help in stabilizing bounding box deviations and prevent abrupt changes that can affect tracking accuracy. The processing time of per frame is monitored to make sure that the system works within the real time constraints. The system obtained an average processing time of approximately 40 milliseconds per frame, and this highlights a real time performance without any noticeable lag.

The effectiveness of the model is further validated through a performance metrics analysis by comparing predicted and ground truth labels for obtaining matrices like true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN). From these matrices the model's accuracy, F1-score, recall and precision was analyzed. This approach provides a thorough idea of how well the system can maintain accurate identification and tracking of the parathyroid glands under varying lighting conditions. By focusing on these metrics, a clear picture of the system's performance is provided through this evaluation, ensuring that it meets the demands of a dynamic surgical environment. This thorough evaluation process is key to improving the methodology and making sure that it can reliably help surgeons in preserving the parathyroid glands, thereby reducing the risk of postoperative complications.

The proposed **ParaTrackNet** architecture Fig 1, ensures accurate and reliable detection and tracking of PGs during surgical operations, leveraging the capabilities of fluorescence imaging, OpenCV along with ORB feature and Kalman filtering. This method has the potential to enhance the surgical outcomes and patient safety during surgical procedures. The integration of real time video processing techniques with advanced computer vision and deep learning algorithms provides the surgeons with a robust tool, aiding in the precise detection and preservation of critical anatomical structures during thyroidectomy and other similar procedures. This methodological foundation sets the mark for future improvements, including the incorporation of machine learning algorithms for improved detection accuracy and the development of more complicated tracking mechanisms to handle difficult surgical scenarios.

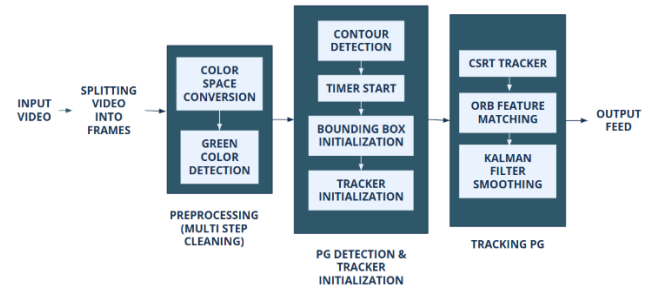


Fig. 1. ParaTrackNet Architecture

The below images (Fig 2 to 4) show the process of the detection of parathyroid before and after Indocyanine green (ICG) is injected.

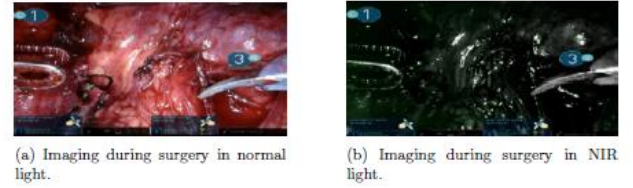


Fig. 2. Comparison of imaging in normal an NIR lighting conditions.

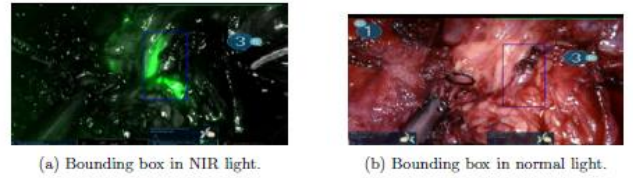


Fig. 3. Bounding boxes in NIR and normal light after PG detection.

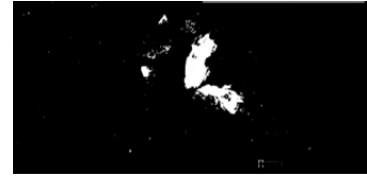


Fig. 4. Mask applied over imaging for clearer parathyroid detection

IV. RESULTS AND DISCUSSION

The analysis conducted on the parathyroid detection algorithm through the provided inputs has yielded insightful results. The confusion matrix demonstrates the models strong performance in correctly classifying instances. Out of the 2081 frames in the input, 1164 were true positives (TP) and 851 were true negatives (TN), the system shows great reliability in differentiating the positive and negative cases. The false positive (FP) rate of 6.5% suggests that a small fraction of negative cases was mistakenly labelled as positive, which may lead to unnecessary follow-ups. The false negative (FN) rate of 0.7%, which is minimal and ensures that almost all the positive cases are detected, which is important for medical applications because missing a true case can have serious consequences.

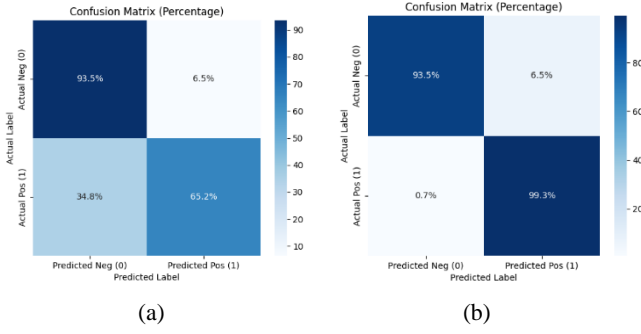


Fig. 5. (a) Confusion Matrix of CSRT Approach Comparing Predicted and Ground Truth Labels, (b) Confusion Matrix of Ensemble Model Approach Comparing Predicted and Ground Truth Labels

TABLE I. CONFUSION MATRIX METRICS AND PERFORMANCE SUMMARY

Metric	CSRT Tracker	Ensemble Model
True Positives (TP)	764	1164
True Negatives (TN)	851	851
False Positives (FP)	59	59
False Negatives (FN)	408	8

At certain timestamps in the video, the tracking model was misaligned from the target area and produced multiple consecutive false positive detections before aligning with the correct segment. Even without the presence of the parathyroid gland, such misguided automated errors would still occur due to strong background autofluorescence, specular reflections, or motion blur from camera panning mid-surgery. These visual artifacts were misleading and created regions that closely resembled the gland in brightness and shape.

For example, between frames 851 to 909, the tracker mistakenly latched onto a nearby bright region, resulting in 59 false positives due to reflective structures simulating gland fluorescence. After frame 909, it corrected itself and resumed accurate tracking, highlighting the ensemble model's ability to recover from drift. This demonstrated the effectiveness of the ensemble approach.

For the remaining parts with noisy frames, the model seems to have regained function and accurately detected and labeled the gland. This result verifies the effectiveness of the proposed ensemble approach, which combined spatial tracking was done with CSRT, feature consistency was tracked with ORB, and temporal smoothing was done with a Kalman filter.

Overall, the model shows high recall of 99.3%, meaning it correctly identifies almost all the positive cases, and a strong specificity of 93.5% which minimizes incorrect detections. These results show that it is a well optimized detection system, but improvements could focus on reducing FP and increase the precision without missing real cases.

TABLE II. PERFORMANCE MATRICES

Metric	CSRT Tracker	Ensemble Model
Accuracy	0.7757	0.9678
Precision	0.9283	0.9518
Recall	0.6519	0.9932
F1-Score	0.7659	0.9720

The performance matrices exhibit the AI-based detection and tracking models' effectiveness, demonstrating its reliability for real time surgical applications. An accuracy of 96.78% was achieved by the ensemble model confirming the model's reliability in distinguishing between glandular and non-glandular areas with minimal errors when compared to the lower accuracy of 77.5% of initial CSRT tracker. This also demonstrates how the Kalman filter improved the model's accuracy and other performance matrices. Its precision of 95.18% ensures that fewer false positive detections occur and which is crucial for preventing unnecessary surgical steps. The recall of 99.32% shows the models ability in detecting nearly all the glandular regions and reducing the risk of missing important structures. The F1 score of 97.20% highlights a strong balance between the precision and recall, making sure that the system maintains consistent performance across different conditions.

The systems performance was further analysed with visual representations in the accompanying graphs for getting better insights. The first figure Fig 6a, "Bounding Box Area over Time," depicts the fluctuations in the area of the detected bounding box across the video frames. The successful detection and tracking of the parathyroid gland are shown by the initial rise in the bounding box area. However, the subsequent variations, notable decrease is observed, indicating challenges in maintaining consistent detection, this due to changes in the lighting condition during the surgical procedure.

The "IoU over Time" figure Fig 6b, shows the Intersection over Union (IoU) metric (above 0.85), a key indicator of the tracker's accuracy compared to the initial bounding box. The high IoU values initially demonstrate a period of stable and accurate tracking, yet the significant dips, point to moments where the tracker loses precision. These drops in IoU is due to the change in lighting conditions and rapid movements, even though the gland is still being followed properly by the tracker in real world output.

Fig. 6c shows consistent processing time per frame, averaging 0.04 seconds. Minor spikes during lighting transitions result from tracker recalibration. Optimizations like fewer ORB keypoints, bounding box tuning, and frame resizing ensured real-time performance without straining computational resources.

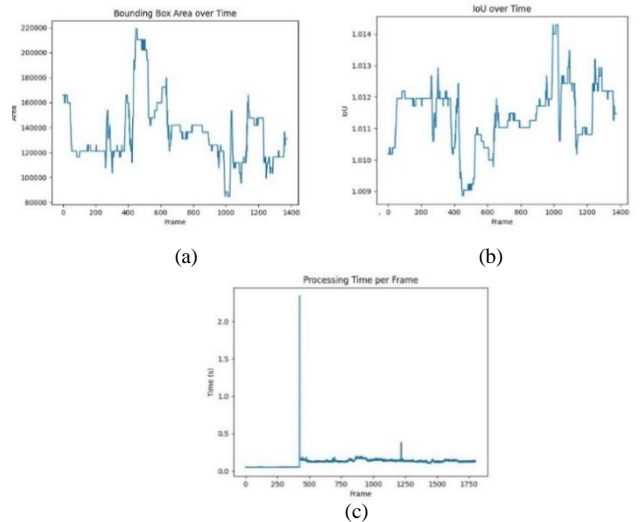


Fig. 6. Visual representations depicting (a) Bounding Box Area over Time, (b) IoU over Time, and (c) Processing Time per Frame

The below images show output of the program where the parathyroid is detected in NIR light (Fig 7a) and normal light (Fig 7b) along with the masked image (Fig 7c)

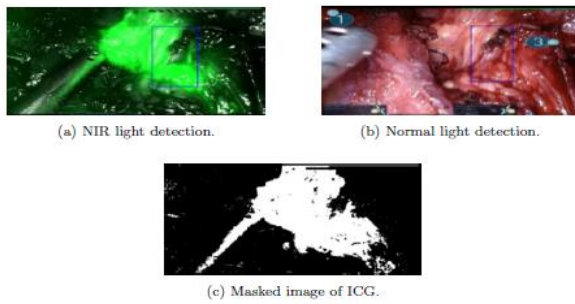


Fig. 7. Comparison of outputs in (a) NIR light, (b) normal light, and (c) masked image

The tracking performance was found to be relatively robust to moderate variations in ICG dosage and lighting calibration. The integration of Kalman filtering and ORB feature matching helped in maintaining detection stability even when the ICG fluorescence intensity varied slightly due to differences in dye uptake or surgical lighting repositioning. However, extreme underdosing or poorly calibrated NIR sources may still lead to detection challenges, indicating the importance of maintaining standardized imaging conditions.

Regardless of the tracking system's occasional false positives and negatives, the ensemble approach guarantees that a patient's safety is not put at risk during an operation. The system acts as a peripheral aid in augmenting the surgeon's sight rather than overriding the practitioner's manual detection and clinical reasoning processes.

In the case of false positives (Fig 8a), where the tracker momentarily highlights a region not containing the parathyroid gland, there is no risk of inadvertent action. These overlays are non-intrusive and purely visual. Surgeons do not act based solely on the bounding box but continue to rely on anatomical landmarks, autofluorescence cues, and direct inspection. Importantly, the proposed system shows quick recovery after such temporary errors, aided by the stabilizing effect of the Kalman filter and the feature revalidation from ORB, minimizing the chance of persistent drift.

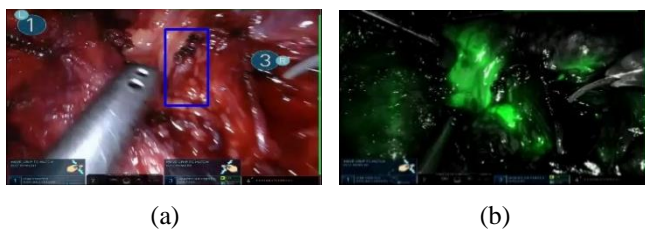


Fig. 8. (a) False positive detection case, (b) False negative detection case

Similarly, false negatives (Fig 8b)—where the gland is briefly not detected—do not hinder the procedure. The high recall rate (99.3%) of the proposed system ensures that such misses are extremely rare, and when they do occur, the model quickly re-aligns with the target. In general, the minimal false detection rates, short durations of misclassification, and real-time self-correction ability of the model, support the idea that the ensemble-based approach presented in this study improves intraoperative guidance without any clinical risk.

ParaTrackNet demonstrates strong performance with high accuracy, stable tracking, and minimal failures. Fluctuations in IoU and bounding box size, mainly due to lighting changes,

reflect fine-tuning rather than errors. The system adapts well to dynamic surgical conditions, with consistent 0.04s/frame processing time, making it a reliable tool for real-time parathyroid detection.

While prior works such as those based on YOLOv5 and U-Net have demonstrated commendable accuracy in parathyroid detection under NIR, the ParaTrackNet ensemble system presented in this study was not directly compared on the same dataset due to model architecture differences and the lack of standardized benchmark datasets for surgical applications. Nevertheless, the proposed system achieved higher consistency under real-time surgical conditions and lighting variability, which remains a limitation for many object detection architectures.

V. CONCLUSION

This paper presented a new real-time AI system, **ParaTrackNet**, for precise detection and ongoing tracking of parathyroid glands (PGs) during thyroidectomy using near-infrared fluorescence (NIRF) imaging augmented by indocyanine green (ICG). The adopted architecture successfully integrated color space transformation, morphological processing, and ORB-based feature extraction with Kalman filtering and CSRT-based Kalman tracking mechanisms to guarantee solid gland localization despite virtual changes in surgical light.

The preprocessing technique proved successful in isolating the distinct green fluorescence of PGs by converting into HSV color space and applying Gaussian blurring to reduce noise and enhance the region segmentation. Fluorescence-based detection technique coupled with contour analysis and morphological operations successfully detected the PGs in NIR frames. Nevertheless, using CSRT tracking alone was not enough in sustaining consistent detection during occlusions and lighting changes. To counter this, the incorporation of Kalman filtering provided predictive tracking, which compensated for lost detections and maintained bounding box stability between frames.

However, while the algorithm performs well under typical conditions, there remains room for improvement even though Kalman filtering improved the tracking consistency and reduced false positives, integrating it with deep learning models like YOLOv5 or MobileNet-based models that are lightweight could improve robustness and detection even in cases of occlusion or anatomical differences. Although newer object detection architectures like YOLOv8 could potentially enhance detection accuracy, their reliance on high computational resources and frame-level object recognition may not offer the continuous temporal stability needed for real-time surgical tracking. In contrast, the CSRT+Kalman ensemble used in ParaTrackNet offers a lightweight, robust alternative that effectively compensates for occlusions and lighting changes through its predictive and smoothing capabilities. Nonetheless, the proposed **ParaTrackNet** architecture offers a resource efficient and practical solution with potential to support during intraoperative scenarios, where consistent and accurate tracking is critical.

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