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Automated Detection and Classification of Necrotizing Fasciitis in Patient Affected Area Images using YOLO v9

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***Abstract*—Necrotizing fasciitis is often regarded as a clinical and surgical emergency characterized by rapid onset, swift progression, and a significant mortality rate. Often because of atypical clinical presentation, the disease evades early diagnosis and subjectively gives way to delayed treatment with an increased risk for severe complications from septic shock and multi-organ failure. This study looks into the possible use of a deep learning model utilizing YOLO v9, which automatically detects NF in images of the affected areas of the patient's body obtained from patients suspected to be infected. Analysis of annotated images dataset, therefore, is primarily targeted at early improvement in detection accuracy with a view to facilitating prompt diagnosis and treatment. Results thus obtained indicate a model boosting the diagnostic precision which would eventually decrease morbidity and mortality rates on matters related to necrotizing fasciitis.**

Keywords - *Necrotizing fasciitis, Deep learning, YOLO v9, Automated diagnosis, Machine Learning, F1 score, Precision*

I. INTRODUCTION

NF, or necrotizing fasciitis, is a rapidly progressive life-threatening soft tissue infection that primarily affects the fascial plane. The public health issue continues to be critical at this present juncture for 2024; close to 10,000 cases are reported in the United States annually. Across the globe, the incidence of NF varies according to regions, yet the mortality rate remains above 30% because of the rapid progression of the disease, along with a rather delayed diagnosis. Mortality exceeds 40% in places where such healthcare is scarce. Early and accurate diagnosis of NF is important to prevent such devastating outcomes.

Since NF is aggressive in nature, it can bring on serious morbidity and mortality unless diagnosed and treated before time. The early challenge for diagnosis lies in the fact that the initial presentation often mimics milder forms of infection, thus creating difficulties for clinicians to differentiate between NF and conditions like cellulitis. Traditional techniques may vary from clinical judgment with imaging and laboratory investigations; both require a time frame and therefore are not very accurate.

In recent years, advances in artificial intelligence, particularly in deep learning, have opened new avenues for improving the early detection of NF.

It is very difficult to detect necrotizing fasciitis at an early stage, mainly due to the fact that NF is clinically nonspecific and progresses rapidly. Although traditional object detection algorithms, such as YOLOv3, are generally applied widely in medical imaging, they are still limited in their ability to capture complex, fine-grained features in some conditions. The latest proper iteration of the YOLO series has been named YOLOv9, which would appear to make significant improvements relative to those presented above, especially focused on detection of subtle signs of NF. YOLOv9 incorporates Transformer layers that allow for handling the spatial relations and high, fine details of a medical image, particularly tissue swelling, skin discoloration, and early necrosis. Upgraded bounding box regression provides the best performance in bounding box localization, which means better detection of small and early-stage lesions. Moreover, the latest version of the YOLO model, YOLOv9, outperforms other variants by a significant margin in multi-scale detection and is therefore appropriate for detection of NF from images where the infection covers only smaller parts of the body.

By leveraging a dataset of annotated images, the proposed model aims to enhance the accuracy and speed of NF diagnosis, potentially reducing the delays associated with current diagnostic methods and improving patient outcomes.

One of the long term goals is that it should be a user friendly and cost effective mechanism for the early detection of NF, whereas the contribution within the current submission is targeted to provide a system development for the purpose of identification of NF at more advanced stages [1]. This is undertaken with people from needy communities who may not benefit from proper healthcare systems in place and would be in considerable need of a free and easily accessible tool. That is to say, early and promising results are found, but the system that can be developed at this stage is far from ready to appear in a clinical setting.

This paper raises a new solution approach which promises high accuracy and efficiency in the detection of NF from medical images. Going above improvements made by YOLOv9, this proposed algorithm utilizes transformer layers in the model and improved bounding box regression in order to capture slight early-stage lesions typical for NF. Our approach is aimed at overcoming some of the shortcomings of the current deep learning models in detecting fine and small details and provides an independent means of diagnosis for patients that are more reliable and timely.

II. LITERATURE SURVEY

We conducted a survey of more than 25 papers and we have recorded our findings from them as listed below.

A. *Diagnostic Challenges and Risk Factors*

Diagnosis of necrotizing fasciitis is challenging, because this disease is highly unpredictable in its presentation and advances rapidly. Early manifestations are often vague, uncharacteristic, and may not present with such common findings as crepitus or skin necrosis. Healthcare providers may not readily diagnose NF in the initial stages from other less serious soft tissue infections like cellulitis or abscesses [2]. **Fais et al. (2018)** described a comprehensive literature review of the clinical and medico-legal challenges faced when dealing with the diagnosis of NF, indicating not only the challenging early diagnosis but also potential law implications from delayed or missed diagnosis. The review further suggested that early detection is the key as any delay in treatment brings catastrophic results including septic shock, multi-organ failure, and even death, with a mortality rate between 20% and 40%. It further underlined the need for more reliable diagnostic tools instead of subjective judgments of clinicians and called for an integrated approach for use of combined state-of-the-art imaging techniques with laboratory markers along with clinical evaluation.

Karnuta et al. (2020) conducted a highly detailed investigation of the demographic and clinical factors contributing to in-hospital mortality among NF patients. Several of their critical risk factors could deepen the condition and aggravate outcomes for the patient further. The elderly represented an important at-risk group, with geriatric patients suffering much for several reasons, including weakening of their immune system and comorbid conditions like diabetes, cardiovascular diseases, and immunosuppression. Most importantly, however, would be comorbid conditions that would be critical, including such cases of chronic renal failure, cirrhosis of the liver, or peripheral vascular disease [3]. The study also establishes that the delay to surgical intervention, which would often have been initially based on either misdiagnosis or underestimation of NF's severity, greatly increased mortality. Their finding thus has a valuable message for practicing clinicians: high-risk patients may best be served with aggressive early intervention-early surgical debridement and broad-spectrum antibiotic therapy-even before a definitive diagnosis can be made.

However, one of the major challenges at the diagnosis stage is that the reliance on a clinical suspicion scoring system calls for very limited predictive accuracy. In fact, **Neeki et al. (2017)** tried to establish how the LRINEC score was effective in diagnosing NF in the emergency setting as a point of differentiation from other soft tissue infections like cellulitis. The LRINEC score is derived from six laboratory values: C-reactive protein, total white cell count, hemoglobin, sodium, creatinine, and glucose [4]. While Neeki et al acknowledged that the LRINEC score had merits in raising high-risk patients, they cautioned against its overuse. Indeed, their research study showed that although valuable, the LRINEC score may produce false negatives in patients whose presentations of NF are atypical, particularly at the onset of NF. The authors acknowledged that the score should only assist, not replace, clinical judgment and that clinicians should continue to be vigilant when the score is low but clinical suspicion is high.

In a similar case, **Wilson and Schneir** issued a 2013 case that showed that the LRINEC score was unable to make an NF diagnosis. In the case report by Wilson and Schneir, the patient had a zero LRINEC score but later diagnosed with necrotizing fasciitis. This case proved that no number-grabbing scale is infallible; this patient had clinical presentations that hindsight had indicated were early signs of NF. The implication of the findings suggested that an LRINEC score of less than or equal to 6 does not exclude NF as a diagnosis, and clinical suspicion should supersede in at-risk patients or in patients with notable findings on physical exam. [5] The recommendation of the authors was the use of adjunctive diagnostic methods like advanced imaging via CT scan, MRI, or ultrasound when NF is clinically suspected but ruled out based on clinical and laboratory studies.

B. *Imaging Techniques and Diagnostic Tools*

Yoon et al. (2019) suggested an integrated MRI finding of the Laboratory Risk Indicator for Necrotizing Fasciitis score in order to develop a more sensitive and even more potent and efficient tool than the original one. Inclusion of MRI made sensitivity and specificity increase high up so as to better distinguish NF from other soft tissue infections. MRI could visualize such minute fascial changes, which included fluid collection and soft tissue edema, leading to diagnostic acumen that had not been available from previous laboratory markers [6]. The hybrid model used here-the traditional scoring systems combined with imaging-looks set to become a new standard for making an early diagnosis of NF, thus negating any chance of misdiagnosis and exploratory surgeries.

Tso and Singh took attention to the lower extremities, as NF is the most common with such localization, determined the value of various imaging modalities used for such entities. The imaging markers identified in the study were the critical signs for NF: gas formation in soft tissues, fascial thickening, and fluid tracking along fascial planes. They have been proven to often appear on CT scans and MRIs, thus forcing clinicians to make decisions more based on facts and faster [7]. The study further highlighted that while the same applies for both CT and MRI, MRI proved a far more reliable technique in viewing changes in soft tissues. However, MRI tends to be rather expensive while less accessible in emergency rooms than CT. Therefore, a balanced approach using CT in early-stage suspicion and MRI for detailed diagnosis is often recommended.

Carbonetti et al. (2016) compared the efficiency of contrast-enhanced computed tomography and the LRINEC score in the early detection of NF. The study proved that although the LRINEC score is a good initial assessment tool for predicting the risk of infection, CT scans bring more details to the depth of infection, particularly in visualizing the presence of gas within soft tissues and fluid collections, which are two classic signs of NF [8]. The study concluded that CT is highly useful in early detection when clinical signs are vague or incomplete. However, CT has the disadvantage of not being able to be used in early-stage NF because tissue changes might not yet be conspicuous. This makes clear the importance of using more sensitive imaging techniques or even additional diagnostic tools in order to diagnose this infection as soon as possible.

Hsiao et al. (2020) established the utility of applying the LRINEC score in patients with NF that affect the limbs, based on a prospective study. Although their results confirm the practical application of the LRINEC score, especially among the most at-risk cases, the score is not a convincing diagnostic tool. Imaging tools, such as CT or MRI, can be used with the LRINEC score by Hsiao et al. to improve diagnosis. The article shows that these tools can be used in combination significantly to minimize false negatives and prioritize patients for urgent surgical intervention [9]. The laboratory markers along with imaging findings in the diagnostic processes make NF diagnosis less subjective to clinical judgment.

Emerging diagnosis tools, like sonography, are also considered as promising tools for rapid and non-invasive detection of NF, particularly in emergent settings. **Clark and Fisher (2017)** demonstrate the utility of ultrasound in the detection of NF; to be more precise, it may effectively be able to identify fascial thickening, fluid accumulation, and gas bubbles among themselves, forming a cornerstone for infection identification. Ultrasound has several advantages: it is widely available, portable, and can be quickly performed at the bedside, making it an excellent choice for use in critical care or resource-limited settings. However, ultrasound is operator-dependent and does not always provide the detailed information needed for a definitive diagnosis; this is most particularly true for deep tissues, in which MRI and CT are greatly superior [10]. It is still a useful tool, albeit for early screening only, particularly at times when more advanced imaging modalities are not available.

Goh et al. (2014) finally concluded that early diagnosis plays an important role in improving the care of patients with NF. Their literature review related to the various methods of diagnosis reflected how long traditional methods had failed to properly care for numerous patients and what justified the development and introduction of more accurate methods of diagnosis such as imaging procedures and laboratory tests. As an extension, they realized the scope of revolutionizing NF detection algorithms through machine and deep learning [11]. **Goh et al.** proposed an integrated approach that would merge imaging, laboratory data with AI to deliver the accuracy needed in the early diagnosis of NF, thereby enhancing survival and lowering surgical intervention severity.

Deep learning has revolutionized image classification and object detection in the medical domain with the use of YOLO and other CNNs. It has had many successful uses of CNN-based models to detect skin conditions, for example, melanoma and psoriasis, where minute skin abnormalities need to be precisely identified. For instance, **Esteva et al. (2017)** demonstrated the applicability of CNNs for classifying images of skin cancer through dermoscopy with dermatologist-level accuracy, thereby raising a possible role for deep learning models in clinical decision-making [12]. YOLO-based models have been used for diabetic retinopathy detection, thereby pointing to their efficiency in localizing affected regions within images.

Given the success of these models in dermatology and ophthalmology, extending the YOLO approach to detect NF, a condition similarly visually manifested, does make sense. However, the largest problem relates to the scarcity of annotated medical datasets for NF. Because NF can present in so many dramatically different ways, large, standardized datasets are challenging to establish for this disease whereas most common skin diseases have well-defined established datasets. The advancement related to YOLOv9's object detection like its superior feature extraction and bounding box regression capabilities can open up the possibility of crossing existing limitations in NF diagnosis to have an even more reliable real-time support during the clinical environment [13].

III. METHODOLOGY

One of the most popular techniques used nowadays in machine learning is object detection technique. Since understanding of an image is demanded, a simple classification of images will not work here and there arises the necessity to clearly determine the concepts along with the location of objects included in every image. Object detection finds multiple applications in various aspects as it can give information that helps in the semantic interpretation of images and videos [14]. There are a number of determinants that establish the precedence of object detection over an image classification method. Image classification allows us to classify an image for binary or multi-class only, by analyzing a whole image, this method will just predict whether the image falls on the particular class or not.

Object detection can not only classify the image but can also recognize which part of an image contains that particular object. Therefore, it further facilitates the localization of the object as well. Object detection works really well in real time. For instance, a user can take a picture either from his or her phone or through any web camera. The relevant object detection model will immediately identify the objects in real-time present in the captured image. Object detection also presents an easier method of identifying multiple areas affected by a single image.

A. *Machine Learning Algorithm*

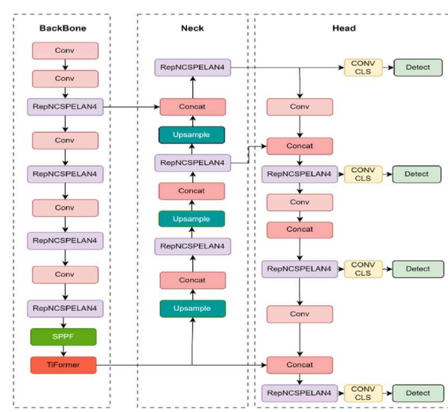
The time taken to complete each task in a particular order is specified. As the description of the task suggests, the YOLO detection algorithm focuses on real time classification of objects by combining its core components effectively. Similar to the objectives of the current work, the first objective of the paper was to incorporate the One-Pass method in order to speed up the computation. This method on the other hand, is different from the old ways of working where the processing was done in steps, with smaller portions of the image being processed at a time. A mesh grid with a weight that is within an acceptable frame size is utilized, assisting in predicting many bounding boxes as well as class probability vectors for each grid cell at the same time. As for the single pass over the entire image towards object deposition, with the benefits of YOLO, this process allows to attain real time detection. It does not segment the regions first

and then use convolutional networks to develop over them rather it seeks to analyze the complete image at once. So, this is one of the reasons why the grids in this instance define a wherever an object detection as well. Therefore, it wouldn't be wrong to say that due to this simple and fast structured design, YOLO would be within a position to carry out the assessments in a shorter while compared to its market peers. In application, it is hence appropriate for tasks that involves intensive and fast object detection, such as self-driving cars, security systems, or medical imaging.

In addition to leveraging YOLOv9 for the detection of necrotizing fasciitis symptoms from patient skin images, we also incorporated YOLOv8 into our experimental pipeline to establish a comparative baseline and evaluate the performance gains achieved through newer model architectures. YOLOv8, known for its balance of accuracy and speed, was trained on the same curated dataset consisting of labeled images across multiple dermatological conditions, including necrotizing fasciitis. The dataset underwent consistent preprocessing and augmentation procedures to maintain parity across model evaluations.

Our primary motivation in including YOLOv8 was to understand how well a slightly earlier version of the YOLO series, albeit still highly performant, could handle the complexities and visual subtleties of this critical skin condition detection task. Upon evaluation, YOLOv8 demonstrated competent performance across key detection metrics, providing insight into its capacity for handling medical imagery classification and localization. The results captured during validation showed that YOLOv8 achieved respectable levels of precision and recall, along with competitive mAP scores at various IoU thresholds. These outcomes served as a benchmark to assess the improvements offered by YOLOv9, particularly in terms of precision, recall, and mean Average Precision (mAP) across both mAP50 and mAP50-95. While YOLOv9 ultimately yielded superior performance in most metrics—benefiting from architectural enhancements and optimization strategies—the results from YOLOv8 validated the feasibility of employing deep object detection models for non-invasive diagnostic support. Thus, the inclusion of YOLOv8 in our study not only contextualized our primary results but also reinforced the robustness of deep learning-based detection pipelines in clinical imaging scenarios.

Furthermore, the model pruning, quantization, and automatic hyperparameter tuning of YOLOv9 provide for an even faster model and increased adaptability across all applications, from GPUs to on-edge mobile phones and embedded systems. And regardless of whether you're using it in self-driving, medical image analysis, or video surveillance, YOLOv9 allows you to perform optimal performance through its streamlined yet powerful architecture



The fundamental concept behind the YOLOv9 architecture is to pull out feature representations from input images using layers of consecutive convolutions. It begins by applying several consecutive Conv layers that progressively detect low-level features, including edges, textures, and patterns in an input image. These Conv layers provide an image understanding of the basic spatial structure of an image that is critical for object detection. The neck section is designed to allow connection of the backbone to the head and also allow integration of features from adjacent level of the backbone. It works with multiscale feature maps which is important considering that we appear in images of different sizes. For this purpose, several RepNCSP (RepNCSpelan4) blocks analogous to the backbone are included in it. These blocks make sure that the feature maps passed to the head contain rich information without a relatively increasing computational cost.

Concatenation or Concat for short, is one of the operations in the neck. In this operation, the former represents the lower level feature maps less detailly, and the latter operates at the higher level feature maps, integrating them across several layers of backbone. At the neck region of human faces, between fine grain and coarse grain features, there is a connecting feature from curtain to curtain. This multi-scale feature fusion enables the network achieving objectives described in the two above, as well as the capacity of the network perceiving large and small targets. The Neck in addition to concatenation, relies on the Upsampling operation, which upscales small feature maps using convolutional operations. Because identifying patterns is important when it comes to identifying smaller objects in an image, you will need to maintain detail, and upsampling will come in handy.

It's the head of YOLOv9 architecture that makes the final object detection predictions. It takes the feature maps coming from the neck and produce bounding boxes, class predictions and confidence calculated for the detected objects. Extra Conv (convolutional) layers are added to the head, that refines the feature maps through another sequence of convolutions to keep in the most meaningful information for the object detection.

The last output layers in this head are represented by CONV CLS + Detect modules. These layers contain functionality that is concerned with classification and localization. The detection head is responsible for drawing boxes around the object, predicting its class, and estimating how likely the predicted class is to be correct. With these final operations, the head is able to perform object detection in an accurate and effective way which also makes YOLOv9 very fast [15]. This is essential when using YOLOv9 in real timely applications where accuracy and speed are both necessary. Thanks to this multi-stage design that has a strong feature extraction backbone, a neck for multi feature integration and a head for detection, it makes YOLOv9 effective even in detecting very small or highly layered objects.

B. Results Analysis Strategy

Model outputs can be evaluated for the performance of the YOLOv3 model through calculating its True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) which gives certain metrics known as precision, recall, and F1-score as given in Equation 1– 3

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

In this section, TP refers to the number of NF objects rightly detected, FP refers to the number of non-NF objects that were detected yet should not have been, FN refers to the number of NF objects that were not detected and TN equals the number of correct backgrounds [16]. The value of TN is of little use in object recognition technology as it is also in most cases due to the fact that the greater part of the picture contents contains TN and that would make the metric hard to use, hence all metrics that contain TN are not used.

To evaluate the detection performance on the objects, the IoU metric has been determined. It examines the proportion between the "Area of Overlap" and the "Area of Union" with respect to the ground truth box and the predicted box. This metric is very significant within the context of evaluation of object detection, for the results achieved do influence the classification of a detection into TP or not. The threshold value for the IoU was 0.5, which meant that if the model predicted a box with an IoU score larger than or equal to the threshold, there is a considerable overlap between the predicted box and any of the ground-truth boxes. This means the model has successfully found an object and the region under surveillance is reported as a positive object. A mathematical formula above called Equation 4.

$$\text{IoU} = \frac{TP}{TP + FP + FN} \tag{4}$$

We would like to note that there is an additional object detection evaluation metric available and this is the Average Precision (AP) metric as well. The per-object weighted average of the precision curve is termed the Mean Average Precision (Map), which is found in a multiclass object detection framework [17]. In our case, we have only one class which is why the AP immobilizes with the mAP. Several cutoff values can be utilized in performance comparison and AP shows the performance of the model at a single cutoff. Higher the AP score better is the model. Our evaluation metric includes mAP and is calculated at an Intersection over Union (IoU) threshold of 0.5 referred to as mAP50. This AP metric has been covered in Equation 5, 6 & 7.

$$AP = \frac{1}{11} \sum_{r=0.0}^{1.0} AP_r \tag{5}$$

$$= \frac{1}{11} \sum_{r=0.0}^{1.0} p_{in}(r) \tag{6}$$

$$p_{in}(r) = \max_{\mathbf{r} \geq r} p(\mathbf{r}) \tag{7}$$

IV. RESULTS AND DISCUSSION

The model was trained and tested using Google Colab, which allowed the use of a Tesla T4 GPU that had 15.84GB of memory, 12.69GB of RAM, and 68.40GB of disk space. This hardware configuration was able to process images and train the model efficiently using the YOLOv8 architecture. The model was trained for 25 epochs over a necrotizing fasciitis image dataset. The performance of the model was satisfactory including a respectable mAP50 of 64.9% developed using pictures of necrotizing fasciitis. This level of precision highlights the extent to which this model is able to distinguish affected from healthy tissues irrespective of the variability of medical images. The findings suggest that the model can be utilized satisfactorily for detection of diseases at onset stage and assists in picking clinical decisions. The results of the training and validation processes are visualized through various plots and confusion matrices that are detailed below

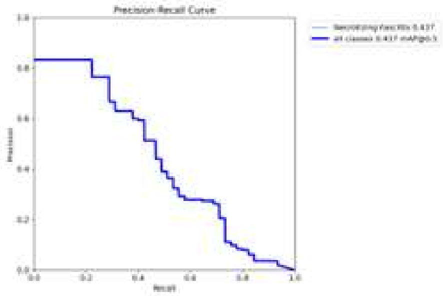


Fig. 1. **Precision-Recall Curve** A Precision-Recall curve is a graphical representation that illustrates the trade-off between precision (the proportion of positive identifications that were actually correct) and recall (the proportion of actual positive cases that were correctly identified) at various classification thresholds. It's particularly useful for imbalanced datasets and scenarios where both precision and recall are crucial, such as medical diagnosis or fraud detection.

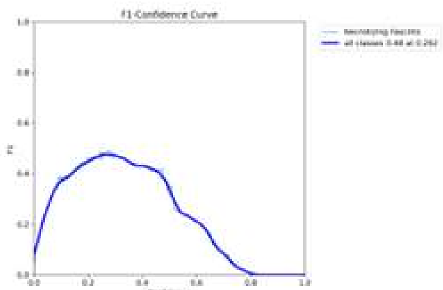


Fig. 2. **The F1 measure** is a metric of effectiveness defined in relation to both precision and recall as their harmonic mean, and is represented in terms of its chronological sequence to visualize the trade off that is achieved through as training continues. The F1-score is particularly valuable in model evaluation because it allows for the incorporation of false positives and false negatives.

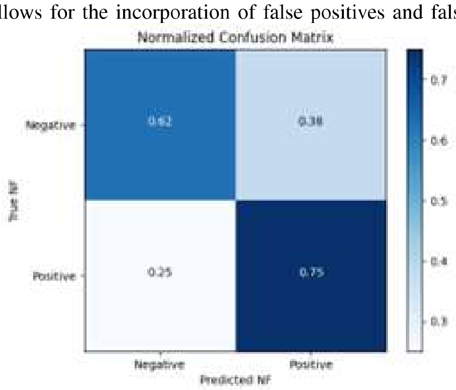


Fig. 3. **Confusion matrix** The confusion matrix visually demonstrates the rate of true positive, true negative, false positive and false negative in the study. This is particularly helpful in evaluating the performance of the model in terms of making correct classifications and understanding which areas the model has missed making a case for (false negatives) or incorrectly encased as case (false positives). The matrix shows how much more successful the model has been in learning the positive and negative cases with most predictions being made as true positive and true negative.

V. CONCLUSION

This research made use the YOLOv9 object detection model to identify patients with Necrotizing Fasciitis (NF). This dataset has been gotten from [1] for this problem. The dataset contains a total of 693 images, all containing images which are raw, augmented and images which are non NF. The dataset created was used to reconcile training a machine learning technique for NF detection. The highest IoU score of 64.9% was found with the dataset settings where all types of images (raw and augmented, non-NF "mixed" images) were employed. Still, these have to be enhanced considerably in view of what is done in real practice in terms of using this model.

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