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Using deep learning for the detection of UFOs within the JET tokamak

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ABSTRACT

Components on the inner wall of fusion reactors are exposed to extremely high heat loads, and significant care must be taken to minimize the damage to these components during operation. UFOs, also known as transient impurity events, are small particles of dust within the tokamak vessel that can lead to plasma disruptions. These can cause serious damage to the device and remain a significant challenge for safe operations. This study presents a novel approach to track these UFO events by utilizing visual camera data from the Joint European Torus and a Convolutional Neural Network to identify UFOs within the tokamak. The model attained an accuracy of 95.1%, a precision of 95.4% for UFO detection, a recall of 95.1%, and a receiver operating characteristic curve area of 0.99. These metrics underscore the model's competence in reliably identifying UFOs with minimal false identifications. Consequently, this suggests the model's suitability for integration into UFO detection systems in tokamak environments, improving monitoring and efficiency, and potentially providing an avenue for real-time UFO detection in future research.

I. INTRODUCTION

A. Background

Magnetic confinement fusion devices, such as tokamaks, are a leading candidate for commercial nuclear fusion energy production.[1,2] The Joint European Torus (JET) is one of the most advanced tokamaks to have operated in the world, holding the record for most energy produced in a single shot and reaching temperatures of 150×10^6 K.[3] With these high temperatures, great care needs to be taken to protect components within the vessel. While the plasma is typically confined by magnetic fields to focus heat flux onto the divertor tiles while avoiding contact with any other first-wall components, any unexpected loss of this confinement can lead to huge heat loads being deposited onto these components, potentially causing serious damage.[4] Due to this risk, the plasma must be monitored carefully, with the real-time protection system evaluating the tile temperatures during a pulse, and diagnostics investigated by the machine operators after a pulse.[5]

Within the JET vessel, there are over 25 cameras positioned in strategic locations to monitor the plasma in real time during an experiment,[6] with the exact number changing depending on the experiment being performed. These cameras include visible spectrum cameras to produce a view of the actual state of the plasma, infrared spectrum cameras to measure the temperatures of wall segments and divertor tiles,[7] and high-speed cameras to detect rapidly changing phenomena.

During operation, there will be a visual systems operator (VSO) present in the control room, who will be responsible for reviewing the images from the previous pulse to confirm that it caused no damage to the machine.[8] The VSO also monitors the presence of UFOs (or transient impurity events) within the vessel, examples of which are shown in Fig. 1. These are usually small particles of dust dislodged from tiles within the vessel, most commonly made of either W (tungsten from divertor tiles) or Ni/Fe/Cr (from inconel or steel), which can lead to a significant spike in radiated power.[9] Witnessing a small number of these events during operation is considered normal and does not have a significant effect on the plasma. However, a high influx of UFOs can introduce impurities into the plasma, potentially leading to instabilities and compromised confinement due to radiative temperature losses. Additionally, larger UFOs pose a substantial risk of inducing a sudden thermal quench, escalating the likelihood of a disruption. Such events have the potential to inflict severe damage on the machine.[10]

The VSO uses the JUVIL (JET Users Video Imaging Library) system within the control room to review video data, and can also use this software to create entries into a "logbook" if significant events are witnessed.[8] The VSO will typically use their judgment to create a log for any significant UFO events that they have identified. Due to the fast-paced nature of each session and the manual interpretation involved, it is possible that the VSO will miss or otherwise not create a log entry for some potential UFO events. A successful session will see a pulse approximately every 20 min. During each pulse, the VSO must review data from all protection cameras, check any alarms that were triggered by the real-time protection system, check maximum temperatures reached in any regions of interest, enter any concerning temperatures into the logbook,[5] and report any issues to the session leader.

B. Problem statement

UFO events are inherently difficult to monitor and account for during operation, since debris becoming dislodged from a tile is difficult to predict. They are also difficult to identify and categorize without human intervention, as they typically vary wildly in size, location, and appearance. As they have been observed to trigger disruptions,[10] any method that can be used to keep track of these events is crucial so that the risks are properly understood. Alarms can be configured using the PETRA (Plasma Event TRiggering for Alarms) real-time protection system[11] to terminate pulses with unexpected increases in the fraction of radiative power, but these alarms have a high assertion time and so would miss rapidly changing phenomena such as UFOs.

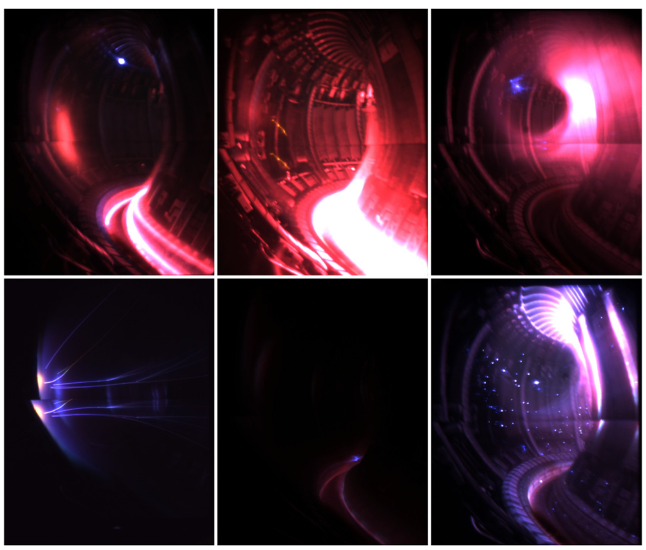


FIG. 1. Examples of frames of JET pulses corresponding to a UFO event from camera KLDT-O5WB. These can happen at any time during the pulse, and appear in a range of sizes, positions, colors, and quantities. From top left to bottom right: pulse 103152, frame 248; pulse 99965, frame 378; pulse 98006, frame 160; pulse 94366, frame 55; pulse 99516, frame 106; pulse 98197, frame 348.

This paper proposes training a Convolutional Neural Network to automate the process of the detection and logging of these events, referred to as "ENEJETIC" (Enhanced Neural Engine for JET Image Classification). It is trained using frames corresponding to logbook entries, which have been created by VSOs over the past 5 years of experiments, with the dataset subsequently being quality controlled and expanded by trained VSOs. While other detection techniques could be used, such as monitoring for spikes in the level of impurities in the plasma or in radiative power,[12] these would likely not be able to reliably identify small or dim UFOs. An approach employing a CNN should allow for the detection of UFOs that appear with a wide range of physical characteristics, so long as the training set is expanded to cover as many cases as possible.

This solution would reduce the workload on the VSO in the control room, as they would be able to review a filtered set of images instead of reviewing all images from the visible cameras. It would also be able to eliminate the inconsistencies in the logging of UFOs between different VSO staff members, meaning that an accurate estimate of the number of UFOs in all historic pulses could be obtained by running the video through the algorithm and logging the results.

C. Previous work

While the number of UFOs observed in JET has decreased by orders of magnitude since the introduction of the ITER-like wall (ILW),[13] a significant number of UFO events are still observed by the VSO in the control room, especially during high-powered pulses. An analysis of unexpected spikes of radiative power showed that 1800 events were detected in 2800 plasma discharges since the ILW was installed.[12] UFOs are also a major concern for other tokamaks. During a campaign on the Tore Supra tokamak, an almost linear increase in the number of UFOs observed per day was recorded, with operational difficulties caused by these UFOs becoming so severe after seven days that the experimental scenario had to be changed.[14] Designers of future machines are also mindful of the impact of UFOs on their operations, such as concerns about the design of SPARC leading to a high number of UFO-related issues.[15]

UFO events have been shown to trigger disruptions. 2.3% of disruptions in JET are caused by UFOs, where different operational conditions, such as changes in plasma-wall interaction and performing high-powered pulses, can greatly increase the incidence of UFO triggered disruptions.[10] On Tore Supra, UFO appearances are given as the main operational issue, with the number of disruptions observed linearly increasing with the number of UFOs observed, and a corresponding linear decrease in the pulse length.[16] In an analysis of the first high fluence campaign performed in WEST, 686 UFOs were detected from 384 discharges, with 133 of these UFOs leading to a disruption.[17] The ability to identify these UFO events is, therefore, critical to reducing the rate of these disruptions, especially if they could be identified in real time during a pulse so that disruption mitigation measures could be deployed effectively.

Machine learning (ML) algorithms have previously been deployed to detect UFOs in tokamak plasmas. An integrated deep learning model has previously been created that uses a range of precursors such as H-to-L back transitions, radiative collapses and UFOs to predict disruptions. This algorithm achieved on average 84% correct identification across all event types, but for UFOs, it could only achieve a true positive rate of 60% due to the relative lack of training data (only 7% UFO occurrence in the training dataset).[18] Deep learning has also been used on images from infrared cameras inside the WEST tokamak to automate the identification of thermal events on the first wall and divertor. This gave good performance for events such as radiated heat flux or hot spots, but not on UFOs, which require sequences instead of still infrared images.[19,20] A method dedicated to UFO detection in infrared sequences is in development at WEST.[21] Image processing techniques have also previously been deployed to attempt to identify MARFEs (multifaceted asymmetric radiation from the edge[22]) and UFOs in JET image data, which had an accuracy of over 80% for MARFEs.[23] The algorithm required the analysis of multiple sequential frames to distinguish UFOs from hotspots and is said to be able to correctly identify UFOs in test samples. However, not enough data on UFOs was present to produce comparable statistics to MARFEs. Further work has been performed to improve the accuracy of detection of MARFEs by integrating other diagnostics into the model,[24] but no such work was conducted for the detection of UFOs. More generally, a range of ML models have been developed to predict disruptions in JET. Among the best performing are the Advanced Predictor of DISruptions (APODIS)[25] and the Signal Predictor based on Anomaly Detection (SPAD),[26] both of which were used to predict disruptions in real time.

II. METHODOLOGY

A. Data collection

The visible spectrum camera KLDT-O5WB[27] was selected to collect training data for this study, as it had the most UFOs logged by the VSOs in the control room. At the time of training, there were 914 logs of UFOs on this camera, with the first being recorded in August 2018 (pulse 92 812).

The VSO will usually only log one frame of a pulse as containing a UFO, even if that UFO event spans multiple frames. To maximize the number of frames in the training dataset, and allow for quality control of the logged frames, the Tokamak Recognition and Graphical Extraction Tool (TARGET) was created as shown in Fig. 2. This GUI allows a trained VSO to load, in turn, each frame highlighted by the logs for a given camera, and categorize it as a major UFO, minor UFO, or no UFO. Examples of these are seen in Fig. 3, and definitions of each category can be found in Table I. The VSO can then scroll through other frames in the same pulse video, adding any that contain UFOs to the training dataset. This allowed an increase in our overall dataset of UFO frames to 2936 frames, with 1539 of those showing a major UFO. An equally sized set of non-UFO frames was then collected by sampling randomly from pulse videos included in this study, and reviewing them using TARGET to remove any UFO frames.

TABLE I. Definition of minor and major UFOs.

Characteristic	Minor UFO	Major UFO
Brightness	Faint	Strong
Size	Small	Large
Definition	Blurred edges	Well defined edges
Duration	Single frame	Multiple frames

FIG. 2. The TARGET GUI, with the frame corresponding to a VSO log for pulse 102885 loaded. Users can then categorize this as either a major or minor UFO and add it to the dataset. They can then cycle through other frames in the same pulse to identify additional UFOs, before moving to the next pulse.

B. Camera data retrieval and processing

JET camera data are stored using the JET Pulse File (JPF) system.[28] JUVIL[8] was used as an interface to the JPF camera data, which can retrieve a camera frame given a camera, pulse number, and frame number or timestamp. The UFO logs and supplementary material recorded using TARGET encompass pulses in the range 92 812–104 775. JUVIL was used to assemble the training data by obtaining each frame marked as containing a UFO by the VSOs.

Over time, the data for the visible spectrum camera, KLDT-O5WB, has varied in resolution between 1024×1280, 912×1152, and 696×872. The number of frames at 696×872 was negligible. The frames at 1024×1280 recorded identically sized images to those at 912×1152, but with an additional region of black on the bottom and right. To assemble a uniform set of training data, we discarded

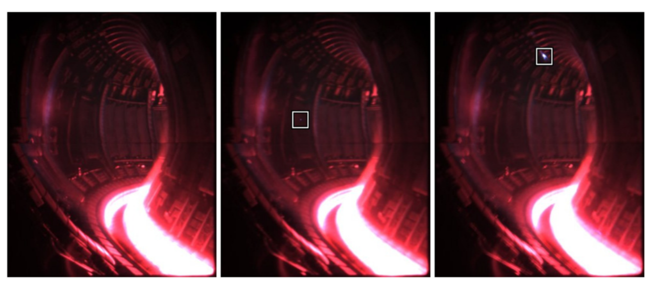


FIG. 3. Example of frames from video of JET pulse 104522 corresponding to a non-UFO (left - frame 268), minor UFO (middle - frame 289), and major UFO (right - frame 294) event. UFOs have been manually highlighted with a white square. These are captured from the JET visual wavelength protection camera, identified and categorized using TARGET, and used for training the CNN model.

frames of size 696 × 872, and cropped the frames at 1024 × 1280–912 × 1152, discarding the black region on the bottom and right side of the images. Additionally, we also discarded a small number of frames, which did not have color data available. The final set of 912 × 1152 images and 1024 × 1280 images cropped to 912 × 1152 were used for training and testing the model.

III. DEEP LEARNING MODEL

A. Model architecture

The core of our UFO detection system is a CNN designed specifically for intricate image analysis tasks, which was created using TensorFlow.[29] The model's architecture includes five convolutional layers, each followed by a rectified linear unit (ReLU) activation function and max-pooling layers to reduce spatial dimensions and extract the most relevant features. These layers are followed by fully connected dense layers, which integrate the extracted features and enable the final classification. The final layer uses a sigmoid activation function as a binary classifier to produce a probability distribution over the possible classes: UFO and non-UFO.

B. Training and validation

ENEJETIC was trained in three iterations, each using equal numbers of UFO and non-UFO images. The first iteration was using a set of 715 UFO frames, which corresponded to the frames specified in the VSO logs only, with erroneous frames removed by a manual review. The next iteration was on the full 2936 UFO frame dataset produced by TARGET; however, this caused issues due to the limited compute power available and the inclusion of the minor UFO frames, leading to a high number of false positives. Finally, the CNN was retrained on only the major UFOs dataset produced by TARGET, giving a dataset of 1539 high quality UFO images. The model was trained using a categorical cross-entropy loss function and optimized with the Adam optimizer,[30] chosen for its efficient handling of sparse gradients.

Once our final dataset and model architecture had been determined, the final CNN model was trained on the CSD3[31] high performance computing cluster. This cluster uses Nvidia A100 GPUs, which allowed an increase in the image size and batch size used during training due to the higher memory available. The dataset was separated into a training set, validation set, and test set, using a 70%–20%–10% split. The model was therefore trained on 70% of our dataset of major UFO and non-UFO images. The accuracy, defined as the proportion of correctly classified frames, and loss, defined as how far the predictions are from the true values, were evaluated after each epoch on the training and validation set of images. To prevent overfitting, we stopped training the model when the training and validation accuracy or loss began to diverge.

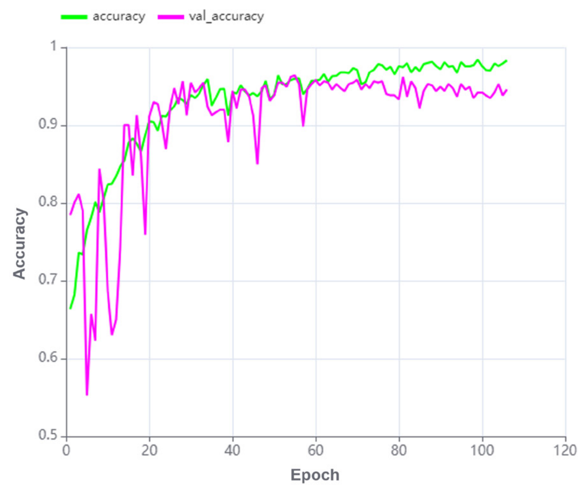
To keep track of the accuracy and loss during training, the tracking and monitoring tool Simvue[32] was used, which allowed the impact of tweaking parameters of the model to be quickly analyzed. The accuracy and loss values reported by TensorFlow during the training of the final model can be seen in Fig. 4, where "accuracy" and "loss" represent the scores achieved when evaluated against the training dataset, and "val_accuracy" and "val_loss" when evaluated against the validation dataset.

IV. RESULTS

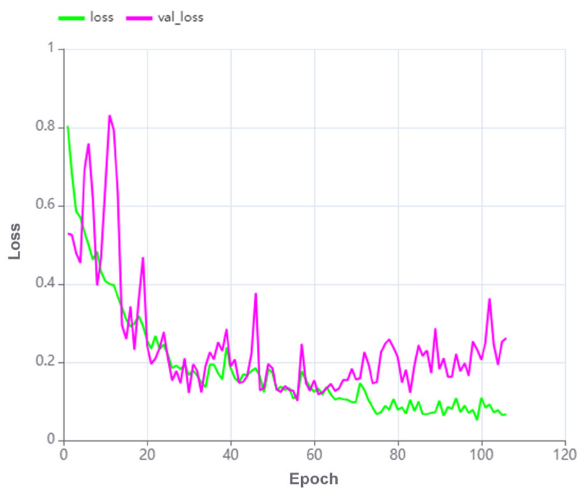
A. Performance

The performance of the ENEJETIC model was rigorously evaluated using a test dataset comprising 10% of our total frames (153 UFO frames and 154 non-UFO frames). These frames were unseen by the model during training, giving an accurate representation of its ability to detect UFO events within the JET tokamak environment. Key evaluation metrics include accuracy, precision, recall, F1-score, and the receiver operator characteristic (ROC) curve area, providing a robust assessment of the model's performance. Table II presents a summary of these metrics.

The model achieved an accuracy (proportion of all classifications which were correct) of 95.1%, indicating a high overall effectiveness in



(a)



(b)

FIG. 4. The measurements of accuracy (a) and loss (b) are recorded after each epoch during the training of the ENEJETIC model, using the set of major UFO frames.

TABLE II. Performance metrics of the ENEJETIC model when validated against an unseen set of images, the number of which is given by the "support".

Metric	Non-UFO (0)	UFO (1)	Weighted avg
Precision	99.3%	91.6%	95.4%
Recall	90.8%	99.4%	95.1%
F1-Score	94.9%	95.3%	95.1%
Support	153	154	307
Accuracy		95.1%	

distinguishing between UFO and non-UFO frames from the visual camera data. The precision (the proportion of UFO classifications which were actual UFOs) was 91.6%, demonstrating that the majority of frames identified as UFOs by the model were correct, thereby reducing the likelihood of false alarms. Recall (the proportion of all actual UFOs which were correctly classified as UFOs) was recorded at 99.4%, reflecting the model's capability to capture the majority of true UFO instances and ensuring that critical events are less likely to be missed. The F1-score (the harmonic mean of precision and recall) was 95.3%, indicating a balanced performance in terms of precision and recall.

For the non-UFO class, the model achieved a precision of 99.3% and a recall of 90.8%, with an F1-score of 94.9%. These metrics illustrate the model's proficiency in accurately identifying non-UFO frames while maintaining a low false negative rate.

The confusion matrix and ROC curve, shown in Fig. 5, give a visualization of the model's performance. The confusion matrix shows that the vast majority of predictions of both UFO and non-UFO frames made by the model are correct, with minimal false positives or false negatives. The area under the ROC curve (AUC) was determined to be 0.99, illustrating the model's exceptional ability to differentiate between UFO and non-UFO frames. An AUC close to 1.0 signifies a high level of discrimination between the two classes.

B. Demonstration

To demonstrate the effectiveness of the algorithm, images for a full pulse video were passed through the model. This is important to test since frames from a pulse video will produce a significantly imbalanced dataset, with most frames being non-UFO classifications. Therefore, to be of use within control room environments, our model must be able to perform in these scenarios while producing minimal false positives. The pulse 104 522[33] was chosen for this, which is the pulse that currently holds the record for the most energy produced in a fusion reaction.[3] This pulse was not logged as containing a UFO by the VSO at the time of the pulse, and, therefore, no images from the pulse were included in the training of the model. Frames from between the times of 40.6s and 53.5s were considered for this pulse, as this was the time from pulse initialization to termination. This corresponds to a set of 322 images.

To create a dataset to compare our model's results against, the full pulse video was loaded into the TARGET GUI, and a trained VSO reviewed the images to identify frames that contained either major or minor UFOs. This was done by a VSO who was external to the development of the model and without seeing any of the results, to avoid introducing bias into their conclusions. Since the determination of what constitutes a major or minor UFO will differ depending on the VSO, examples of major and minor UFOs were provided as shown in Fig. 3, along with the classification guidelines outlined in Table I. If multiple minor UFOs are present in a single frame, this is classified as a major UFO event.

The expert VSO identified 32 frames containing a UFO within this pulse, with 7 of these frames being a major event. It took approximately 10 min for the VSO to label this pulse to this level of detail, which would be unachievable under the time constraints in the control room during operations. The full set of 322 images from the pulse were then passed through the ENEJETIC model to obtain our predictions, taking 34.1 s. Since the final model was trained only on major UFOs, it was anticipated that it would perform better at the prediction of the major UFOs, and be less accurate in identifying minor UFOs.

The model was able to correctly identify 27 of the 32 UFO events, giving a recall of 84%. It was also able to correctly identify all of the major UFO events. The model has a low false positive rate, giving a

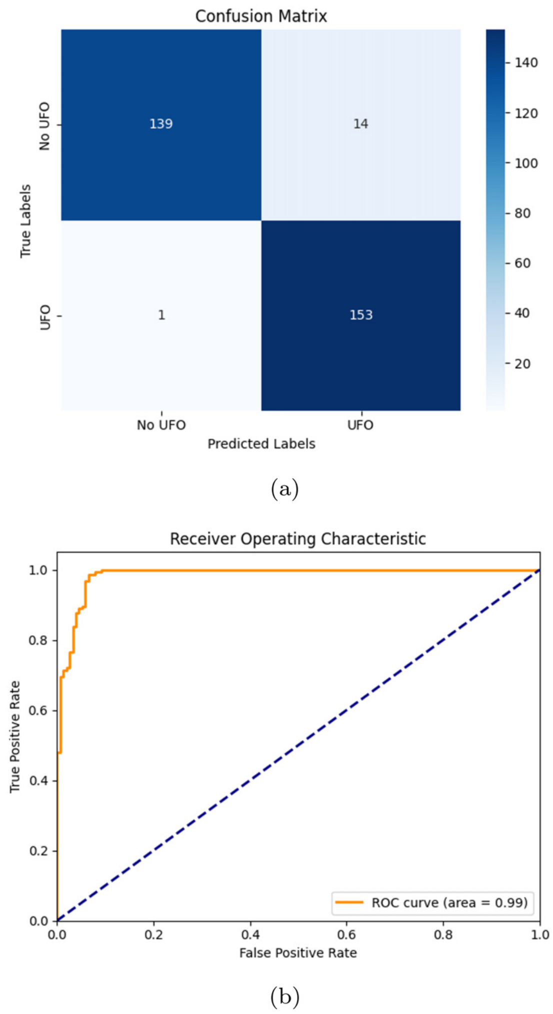


FIG. 5. (a) The confusion matrix for the model, showing a high number of correct classifications. (b) The receiver operator characteristic curve for the model, with an AUC of 0.99.

precision of 87%. The false positive and false negative images were then reviewed individually to understand the areas in which the model was struggling to correctly identify UFOs.

Since there is no hard definition for what constitutes a UFO, there is some scope for disagreement between observers. After carefully reviewing the four false positive frames, two were determined to actually contain (very small) UFOs. Additionally, of the five false negative frames, one was determined to, in fact, not contain a visible UFO. These frames are shown in Fig. 6. After correcting these, the model was found to have an overall accuracy of 98.1%, with a precision of 93.5%, a recall of 87.9%, and an F1 score of 90.6%. These results demonstrate that the model has the capability to be a powerful tool in the detection of UFO events inside a tokamak.

V. CONCLUSION

This study presents a novel application of a CNN for the detection of UFOs within the JET-ILW tokamak, leveraging the visual camera data. The model's high accuracy, precision, recall, and AUC metrics validate its robustness and reliability in identifying UFO events, with an accuracy of 95.1%, a precision of 95.4%, a recall of 95.1%, and an AUC of 0.99, respectively.

ENEJETIC's strong performance when compared with a human VSO demonstrates that it can significantly reduce the potential for false alarms. By automating the detection of UFOs, the model is able to determine the number of UFOs on any historic pulse, allowing for the analysis of quantitative relationships between experimental scenarios and UFO frequency. A human-in-the-loop architecture could be implemented, where the model accurately identifies the majority of UFO events in a pulse and passes them to a trained VSO for confirmation, allowing larger and more resilient datasets to be rapidly constructed. The performance metrics suggest that the model can enable more efficient and timely responses to UFO events in tokamak operations than relying on human expertise alone.

Moreover, the success of this model establishes a foundation for future research into disruption prediction and mitigation. To further develop this work, there are several possible areas to investigate that will allow for its implementation in tokamak safety systems:

- **Transfer and Active Learning:** This model was trained on data from the KLDT-O5WB camera within JET, but could be used as the starting point for the development of a model that incorporates data from other cameras inside the vessel. This could then be extended to build models using camera data from other tokamaks, expanding these datasets using an active learning approach.
- **Object Detection and Tracking:** By adding enhancements to the TARGET GUI, a VSO would be able to quickly draw boxes around the UFOs within the dataset already created. This information could then be incorporated into the model to allow the CNN to identify the position and size of UFOs within the image. For UFOs present in consecutive frames, it would also allow the CNN to be able to track the movement of these phenomena.
- **Disruption Mitigation:** By utilizing records of which JET pulses ended in disruptions, the model can detect pulses where a UFO was present in the frames immediately prior to a disruption. By incorporating the object detection capability described above, a relationship between the size or quantity of UFOs, their position in the tokamak and the likelihood of a disruption being triggered can be derived. This can then form the basis of a mitigation tool, where the model analyses images from a pulse in real time, detects any UFOs, and estimates their likelihood to trigger a disruption. If required, this would then trigger disruption mitigation strategies such as the shattered pellet injector.[34] To enable this, the model's throughput would need to be enhanced—the KLDT-O5WB camera used in this study has a frame rate of 25 Hz,[27] with data available immediately in the shared memory of the data capture PC (where this model could be installed). The model's predictions took approximately 100ms per image in the demonstration on pulse 104 522, so an increase in throughput of at least three times would be required for real time operation.

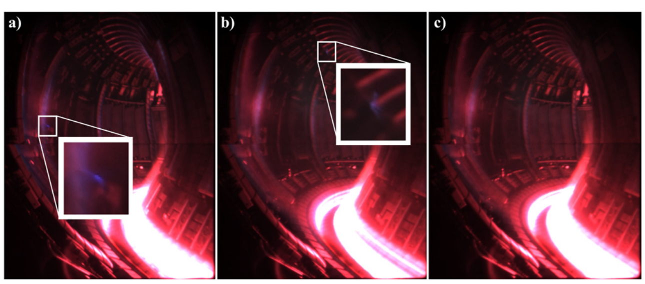


FIG. 6. Frames that were identified as having incorrect labels in the manual review dataset. Images (a) (frame 250) and (b) (frame 359) were categorized as not containing a UFO by the VSO, but very small UFOs are present and highlighted in white boxes. Image (c) (frame 340) was categorized as containing a UFO by the VSO, but this cannot be seen in the image.

The application of deep learning models in the field of plasma physics and fusion research represents a significant advancement in operational monitoring and safety. By integrating these models into existing monitoring frameworks, it is possible to achieve higher levels of precision and efficiency in detecting and responding to anomalies. This research contributes to the broader goal of making nuclear fusion a viable and safe energy source.

In summary, the deployment of a CNN for UFO detection within the JET tokamak has proven to be highly effective, providing a reliable tool for enhancing operational monitoring and safety. The findings from this study not only demonstrate the immediate benefits of this approach but also pave the way for future innovations in disruption prediction and mitigation, ultimately contributing to the advancement of fusion energy research.

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JET, which was previously a European facility, is now a UK facility collectively used by all European fusion laboratories under the EUROfusion consortium. It is operated by the United Kingdom Atomic Energy Authority, supported by DESNZ and its European partners.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

Matthew Field: Conceptualization (lead); Data curation (equal); Formal analysis (equal); Investigation (equal); Methodology (equal); Software (equal); Validation (equal); Writing – original draft (equal); Writing – review & editing (lead). **Steve Etches:** Conceptualization (equal); Data curation (equal); Formal analysis (equal); Investigation (equal); Methodology (equal); Software (equal); Validation (equal); Writing – original draft (equal); Writing – review & editing (equal). **Daniel Collishaw-Schepman:** Conceptualization (equal); Data curation (equal); Formal analysis (equal); Investigation (equal); Methodology (equal); Software (equal); Validation (equal); Writing – original draft (equal); Writing – review & editing (equal). **Jacob Connors:** Data curation (supporting); Validation (supporting); Writing – review & editing (supporting). **Pedro Carvalho:** Conceptualization (supporting); Data curation (supporting); Supervision (supporting). **Scott Alan Silburn:** Conceptualization (supporting); Data curation (supporting); Supervision (supporting); Writing – review & editing (supporting).

DATA AVAILABILITY

Raw data were generated at the Joint European Torus large scale facility. Derived data supporting the findings of this study are available from the corresponding author upon reasonable request.

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