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Automatic detection of the onset of film boiling using convolutional neural networks and Bayesian statistics

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ABSTRACT

The present article shows that a combination of Bayesian statistics and convolutional neural networks can be used to successfully detect the transition from nucleate to film boiling from visualization, even if the heater is not visible in the visualization window of an on-wire boiling process. Using a trained convolutional neural network to classify boiling heat transfer regimes, this paper builds upon previous studies that show that machine learning algorithms can accurately infer boiling heat transfer regimes from visualization, and proposes the utilization of Bayesian statistics to be able to detect the transition from nucleate to film boiling with arbitrarily large confidence within seconds. Results suggest that the precise detection can be potentially done sooner than conventional temperature measurement sensors such as commercial thermocouples and RTDs. Finally, this paper presents several lower bounds to the time to detection of film boiling deflagration, which indicate that sub-second non-intrusive automatic detection of film boiling may be reached, especially with state-of-the-art machine learning algorithms.

1. Introduction

Boiling is a widely used heat transfer process. However, its thermal performance as a heat transfer mechanism is severely limited by the generally fast, transient, unpredictable, onset of film boiling [1]. Therefore, precise characterization and management of its operational regime is of utmost importance. So far, most studies focus on passive techniques for critical heat flux management, such as on designing heaters with enhanced capillarity to increase the critical heat flux [2–7], or in using fluids with suspended particles that, when deposited on the heater surface, create a highly wetting substrate [8–11]. Recently, there has also been some evidence that graphene nanoplatelets, when deposited on the heater surface, may delay the onset of film boiling by up to hours instead of seconds [12].

On the other hand, active methods for detecting and managing boiling heat transfer, however, are scarcer. Studies using ionic surfactants have shown that nucleation site density can be controlled (i.e., increased or decreased) by applying electric fields to the heater [13]. Electrowetting is also currently under investigation to suppress the formation of a vapor layer [14,15]. Nonetheless, regardless of by how much the critical heat flux can be increased, the eventual onset of film boiling is inevitable at high heat fluxes. In fact, as can be observed from the experimental results by Ref. [5], the uncertainty around the critical heat flux for optimal surfaces is even higher than those for the critical heat flux in conventional smooth flat surfaces, evidence for which can also be gathered from the data collected by several studies concerning boiling of nanofluids [16]. Therefore, at very large heat fluxes, accurate monitoring of the boiling heat transfer regime is necessary to guarantee heater health.

Recently, machine learning research has gained significant traction due to an exponential increase of computational power, and is being widely used for image classification and object identification [17]. Machine learning is also being applied to process high dimensional data in the physical sciences, with applications that include finding governing differential equations that explain certain data [18] to assisting in turbulence modeling [19]. More recently, we have also shown that machine learning algorithms can successfully identify boiling regimes with up to 99% precision [20,21], and estimate heat flux entirely from low resolution visualization with less than 10% error [22].

However, despite the near-perfect classification performance reported in Refs. [20,21], for most applications a 99% accuracy might be unacceptably low – consider, for instance, the classification of boiling regime, which, at 30 classifications per second, would return an incorrect inference every 3 s. Therefore, in this paper, a statistical analysis based on Bayes' law [23] is introduced

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Nomenclature

A	arbitrary event
B	arbitrary event
C	detection threshold
L	trained classifier
N	number of frames
T	true label
P	probability
X	frame

Greek symbols

ε	likelihood that film boiling is occurring
Θ	classification metric

Subscripts

i	index
min	minimum
m	index
n	index
pred	predicted, estimated

Superscripts

(i)	index

Abbreviations

CNN	Convolutional neural network
DSLR	Digital single-lens reflex

to complement the classification-based approach reported in Refs. [20,21], and hence detect the transition from nucleate to film boiling at arbitrarily high confidences from both direct and indirect visualization (i.e., even when the heated surface is invisible in the visualization window). It is shown that the proposed methodology is robust even in the event of several incorrect classifications, and that it can detect both the presence of film boiling as well as its onset within seconds. It is also suggested that while the results presented in this paper are promising, significant improvements can be expected using more advanced machine learning algorithms for object detection and classification, which could potentially reduce the time to detection of the onset of film boiling to a fraction of a second.

2. Methodology

This paper expands the work originally reported in Refs. [20,21], which explored the possibility of automatically classifying boiling regimes from individual visualization frames. In that study, an on-wire pool boiling visualization set-up was presented, and it was shown that it is possible to use machine learning models to interpret individual visualization frames and identify whether the phenomenon depicted in each of them is natural convection, nucleate boiling or film boiling, with high accuracies on the order of 99%. However, as discussed in the introduction, while high, algorithms with these accuracies are still inadequate for many, if not most, industry applications. In fact, if a monitoring system relies on the classification of a single frame, it is expected that their prediction would fail every few seconds, hindering its utility in device health monitoring and hazard mitigation. Therefore, this paper explores the possibility of designing a system that, through continuous visualization, is capable of inferring whether boiling undergoes a transition from nucleate to film boiling. To do that, a convolutional neural network is trained to look at visualization frames and identify whether they are characteristic of film boiling or not, which has also been explored by a previous study [21]. The process of training machine learning algorithms to identify boiling regimes is thoroughly described in previous works by the authors, where over 99% accuracy in detecting film boiling has been demonstrated [20,21].

Now, the methodology proposed in this paper shows that the same trained machine learning classifiers can be used to sequentially infer boiling regimes. Consider, for instance, that a boiling system is under visual observation by a camera. Each acquired frame is fed to the machine learning model, which outputs its prediction of whether the frame is characteristic of film boiling or not. If several sequential frames are classified as film boiling, then the likelihood that film boiling is occurring in the system is high, which is the rationale behind Bayes' law [23].

To demonstrate the operation of a monitoring system using classification algorithms, an on-wire pool boiling experimental set-up used in Refs. [20,21] was employed. The classification algorithm (a convolutional neural network, CNN) was trained on the same data provided by Refs. [20,21]. However, in addition to the original data, new movies of the transition from nucleate to film boiling were captured and then fed to the machine learning model (i.e., the CNN), which then infers the boiling regime of each consecutive frame. Then, Bayes' theorem is applied and, based on the likelihood at the previous frame, on the classification result, and on the performance metrics of the classifier, the likelihood that film boiling is occurring at the present frame can be computed. A flowchart of the process is shown in Fig. 1 – note that the first five processes reported in Fig. 1 are the same used in Ref. [20]. Similarly to Ref. [20], the on-wire pool boiling test section is observed by a conventional DSLR camera at 720p and 30 Hz. Each frame is then transformed to greyscale and downscaled by a factor of 5, as suggested by Ref. [20]. Two types of visualization windows are considered: direct observation, in which the wire is visible to the machine learning model, and indirect observation, in which the wire is cropped out of the observation window.

2.1. Convolutional neural network (CNN)

A convolutional neural network (CNN) is a machine learning algorithm specifically designed for visual pattern identification from images [24]. Similarly to Refs. [20,21], and using the same data, in this paper a CNN is trained to be able to classify pool boiling regimes as film boiling or not film boiling (i.e., natural convection or nucleate boiling). The CNN is implemented in Keras with Tensorflow as backend [25]. The raw image sequences are transformed to greyscale and downscaled by a factor of 5, resulting in 120 px × 196 px frames for direct and 72 px × 196 px for indirect observation. The resulting frames and their labels (i.e., 0 for "not film boiling" and 1 for "film boiling") are fed to the convolutional neural network for training. Training is done by gradient descent using Adam with a learning rate of 10^{-3}, and overfitting is prevented by dropout [26]. In this paper, only two convolutional layers are used, with only one hidden fully connected layer. A graph representation of the machine learning model employed is shown in Fig. 2.

The entire dataset, which has also been used by Refs. [20,21], contains 36,539 frames, where 2,207 are labelled as natural convection, 29,986 are labeled as nucleate boiling and 4,346 are labeled as film boiling. Training data comprise approximately

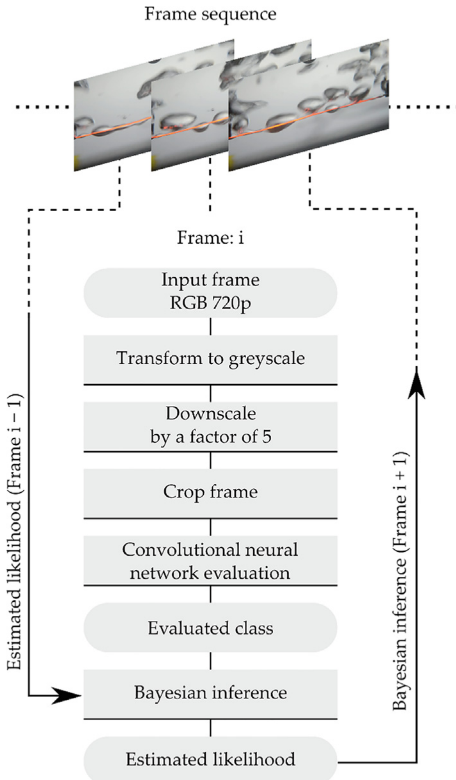

Fig. 1. Flowchart of the proposed methodology.

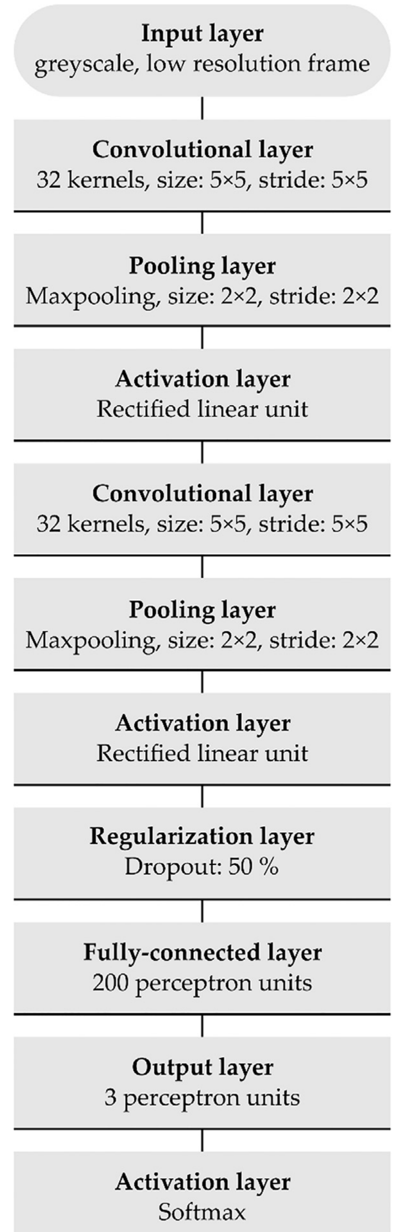

Fig. 2. Graph representation of the convolutional neural network used in this paper.

70% of the dataset, and the test data compose the remaining 30%. After training, the performance of the convolutional neural network is evaluated on the test dataset, for which the results are shown in Table 1 as a confusion matrix.

Table 1, which is often referred to as the confusion matrix [27], shows that, under direct observation, only 2 of all 1,085 film boiling frames (0.18%) were wrongly classified as "not film boiling". Also under direct observation, only 1 out of all 8,050 "not film boiling" frames (0.01%) was wrongly classified as film boiling. Under indirect observation, however, it can be deduced that only 32 of all 1,033 film boiling frames (3.1%) were misclassified as either natural convection or nucleate boiling, and only 4 of the 8,102 non-film boiling frames (0.05%) were wrongly classified as film boiling. It is likely that a parametric analysis of neural network architecture may yield better classification metrics, but such investigation falls out of the scope of the present study, and would likely require larger test datasets for more accurate performance evaluation. However, note that even though the proposed model is accurate (i.e., with 99+% accuracy), it is expected that it will wrongly classify a nucleate boiling frame as film boiling every roughly 10,000 frames, or approximately 333 s if the visualization occurs at 30 Hz. For most industry applications, particularly for those involving hazard mitigation and safety of thermal systems, these error rates are still unacceptable. Nonetheless, as will be shown in the forthcoming sections, this convolutional neural network will be sufficient to detect the onset of film boiling with arbitrarily large precision when using Bayes' law.

2.2. Statistical modeling

Based on the promising, but still limited accuracy of the convolutional neural network of which metrics are shown in Table 1, it will now be shown how Bayes' law can be used to detect the transition to film boiling, and to infer with arbitrarily high precision whether film boiling is occurring.

Table 1
Confusion matrix of the convolutional neural network over the test dataset for direct/indirect observation.

		Evaluated	
		Not film boiling	Film boiling
True	Not film boiling	8049/8098	1/4
	Film boiling	2/32	1083/1001

Let L be a function previously learned by a machine learning model (i.e., the trained convolutional neural network) that outputs whether the model evaluates the frame to be film boiling. In other words, for a given frame **X** – note that **X** is a matrix in which each entry corresponds to the greyscale luminosity of the pixel of its corresponding frame –, then

$$L(\mathbf{X}) = \begin{cases} 0 & \text{if } \mathbf{X} \text{ is not identified as film boiling} \\ 1 & \text{if } \mathbf{X} \text{ is identified as film boiling} \end{cases} \quad (1)$$

In this case, by feeding L a frame, it will output 0 if the trained model identifies **X** as not being film boiling, and 1 if it identifies **X** as being film boiling. Additionally, define a function T that retrieves the true class of a frame **X**, i.e.,

$$T(\mathbf{X}) = \begin{cases} 0 & \text{if } \mathbf{X} \text{ is not film boiling} \\ 1 & \text{if } \mathbf{X} \text{ is film boiling} \end{cases} \quad (2)$$

Naturally, the function T is generally unknown, while L is known by training a machine learning algorithm, as has been thoroughly described by Ref. [20]. Ideally, $L(\mathbf{X}) = T(\mathbf{X})$ for all **X**, which means that the trained model would be able to correctly infer the boiling regime of every frame. As shown in Table 1, this is not the case for the CNN trained in this paper, and is not true in general.

However, if some prior estimation of the likelihood $\varepsilon^{(i)}$ that film boiling is happening is available, then, applying Bayes' theorem, an updated likelihood $\varepsilon^{(i+1)}$ that film boiling is happening can be computed by [23,27]

$$\varepsilon^{(i+1)} = \frac{P[L(\mathbf{X}_{i+1})|T(\mathbf{X}_{i+1})]\varepsilon^{(i)}}{P[L(\mathbf{X}_{i+1})]} \quad (3)$$

where P(A|B) indicates the probability of A given B. For instance, $P[L(\mathbf{X}_{i+1}) = 1|T(\mathbf{X}_{i+1}) = 1]$ represents the probability that the classifier would evaluate the frame as film boiling (i.e., the machine learning model outputs, for a frame $\mathbf{X}_{i+1}$, that $L(\mathbf{X}_{i+1}) = 1$) if film boiling is, in fact, occurring (i.e., $T(\mathbf{X}_{i+1}) = 1$). Note that this probability can be estimated using a suitable test set in which T is known. From Table 1, this metric can be estimated for the CNN that will be used in this paper. For instance, for direct observation, the probability that the learner correctly infers that film boiling is occurring is 1083/1085 = 0.9982. Note, however, that Eq. (3) depends on some prior likelihood that film boiling is happening, i.e., $\varepsilon^{(i)}$ and ultimately $\varepsilon^{(0)}$, which will be updated for each sequential frame.

Now, note that Eq. (3) can be further developed by expanding the denominator, i.e., [27]

$$P[L(\mathbf{X}_{i+1})] = P[L(\mathbf{X}_{i+1})|T(\mathbf{X}_{i+1})]\varepsilon^{(i)} + P[L(\mathbf{X}_{i+1})|1 - T(\mathbf{X}_{i+1})]\left[1 - \varepsilon^{(i)}\right], \quad (4)$$

which is derived from the statistical identity $P(B) = P(B|A)P(A) + P(B|\neg A)P(\neg A)$.

To simplify the abovementioned expressions and to more easily attribute meaning to each term, let

$$P[L(\mathbf{X}_{i+1}) = m|T(\mathbf{X}_{i+1}) = n] = \Theta_{mn} \quad (5)$$

In other words, Θ_{mn} indicates the probability of the algorithm identifying an m regime given that the correct classification of the frame is n. For instance, Θ_{11} is the probability of the classifier evaluating a frame as film boiling given that the frame was in fact captured during the film boiling regime, which is known in machine learning as recall [27], and is the metric that was previously illustrated to being 0.9982 from Table 1.

Using the aforementioned notation, $\varepsilon^{(i+1)}$ can now be written as

$$\varepsilon^{(i+1)} = \frac{\Theta_{m1}\varepsilon^{(i)}}{\Theta_{m1}\varepsilon^{(i)} + \Theta_{m0}(1 - \varepsilon^{(i)})}. \quad (6)$$

Expanding on the previously discussed method to estimate Θ_{11}, the reader should note that, in fact, all coefficients Θ_{mn} can be understood as classification metrics evaluated for a given trained classifier over a suitable test set, all of which can be computed from the confusion matrix shown in Table 1. In fact,

$$\Theta_{mn} = \frac{\text{number of classifications as n when the true class is m}}{\text{number of true m}} \quad (7)$$

These coefficients, for the trained CNN used in this paper, are now shown in Table 2. Once they have been determined, the proposed algorithm does not require any information about the true state of the system other than a current frame, which is the input to the classifier, and the initial prior likelihood $\varepsilon^{(0)}$. Therefore, given that all parameters have been identified, a trained and tested classifier can be used to determine the probability that film boiling is happening, given a sequence of frames, by sequentially predicting the class of each frame, i.e., $L(\mathbf{X}_{i+1})$ and applying Eq. (6).

Hence, in order to recursively determine the probability of whether film boiling is in fact happening, all that is necessary is to know the learner/classifier L and a prior probability of whether film boiling is happening, i.e.,

$$\varepsilon^{(0)} > 0 \quad (8)$$

Note that if $\varepsilon^{(0)} = 0$, then the prediction will always be $\varepsilon^{(i+1)} = 0$. Therefore, it is clear that the prior must be timely chosen in order to calculate $\varepsilon^{(i+1)}$. However, given that the process is recursive, its influence on further iterations is expected to be minimal, as will be shown later.

The process can be better understood as follows:

(a) the classifier/machine learning model is trained and tested on a suitable test set, and all coefficients listed in Table 2 are computed.
(b) A frame sequence is fed to the classifier, which in turn infers whether that frame is film boiling or not. Depending on the output, Eq. (6) is used to compute an updated likelihood of whether film boiling is occurring. This is depicted in Fig. 1.
(c) If at some point the likelihood becomes larger than an arbitrary threshold C, then it can be said with arbitrary confidence that film boiling has been reached. Given that Eq. (6) is strongly dependent on the classifier metrics, namely Θ_{mn}, then the performance of the proposed methodology will naturally depend on the quality of the machine learning model.

3. Influence of classifier performance metrics

In general, the effectiveness of the detection system can be quantified by how many frames N the learner needs to evaluate (or how much time – seconds – are needed) before it can be ensured that film boiling is occurring with an arbitrary likelihood of C. The lower the number of frames N, the earlier the transition to film boiling will be detected by the system. Therefore, this section is dedicated to finding the minimum number of frames N_{min} necessary to detect the transition to film boiling given some classifier metrics.

Mathematically, this is equivalent to, for a given classifier (for which Θ_{mn} and L(x) are hence determined), finding N_{min}, which is the smallest N such that

$$\varepsilon^{(N)} \geqslant C. \quad (9)$$

Given that in practice classifiers have parameters Θ_{mn} that are smaller than one and greater than zero (see Table 2), it is likely that they will, given a sufficiently long frame sequence, wrongly infer

Table 2
Coefficients Θ_{mn} associated with the convolutional neural network.

	Direct observation	Indirect observation
Θ_{11}	0.9982	0.9690
Θ_{10}	0.0018	0.0310
Θ_{00}	0.9969	0.9995
Θ_{01}	0.0031	0.0005

the regime of at least one frame, which would in turn negatively affect the performance of the detection system. Hence, the best-case scenario (i.e., the one that will yield N_{min}) is when the classifier infers the boiling regime of the entire frame sequence correctly.

Therefore, consider the scenario in which film boiling is happening. Hence, it is necessary to make sure that the classifier can, using the previously described recursive algorithm, successfully detect that film boiling is occurring. All relevant learner coefficients, i.e., Θ_{mn} have been determined and the best-case scenario is that the classifier correctly detected that $L(\mathbf{X}_{i+1}) = 1$ for all frames. Then, the number of frames that are necessary to determine that film boiling is happening with at least C certainty is N_{min}.

For given $\varepsilon^{(0)}$ and C, determining N_{min} helps determine the principal parameters that should be optimized when developing and training a classifier for film boiling detection. Note that, if assumed that the classifier will always yield the correct prediction that $L(x_{i+1}) = 1$, then, as per Eq. (6), the only two parameters that influence the prediction are Θ_{11} and Θ_{10}. Hence, Fig. 3 shows N_{min} for $\varepsilon^{(0)} = 10^{-11}$ and C = 0.9999 as a function of Θ_{11} and Θ_{10}. In this case, it is important to note that what is being plotted is, fundamentally, Eq. (6)'s evolution through time, where N_{min} indicates the minimum number of iterations necessary for the condition shown in Eq. (9) to hold. Additionally, the prior $\varepsilon^{(0)} = 10^{-11}$ was chosen sufficiently small so that one would expect film boiling to happen during at most one frame every 1000 years – a parametric analysis of $\varepsilon^{(0)}$ and C will be presented later.

Note that, for low values of Θ_{10}, N_{min} is mostly insensitive to Θ_{11}, which suggests that the influence of Θ_{10} on the number of frames necessary for detection dominates over Θ_{11}. This behavior is expected, given that Θ_{10} corresponds to the probability that the classifier will incorrectly classify a frame as film boiling, when the frame was drawn from another boiling regime. Therefore, if Θ_{10} were high, it would mean that there is a high probability that the frame, which was evaluated as film boiling by the classifier, corresponds to a different regime. Additionally, an important observation is that N_{min} is generally small. In other words, even a relatively bad classifier could potentially detect the transition to film boiling in less than 30 frames, which, for a 30 Hz camera, it should be stressed that this is corresponds to sub-second detection, even if the event is expected to occur with a prior likelihood as low as 10^{-11}.

Hence, consider now the scores for the convolutional neural network under direct observation, as shown in Table 2, in order to analyze the dependence of N_{min} on the prior $\varepsilon^{(0)}$ and on the detection threshold C. The results are shown in Fig. 4. Note that even a very restrictive threshold (i.e., small $1-C$) paired with a small prior does not significantly affect the number of frames necessary for detection. In fact, the difference between the lowest and highest values for N_{min} in Fig. 4 is less than 10, which, when

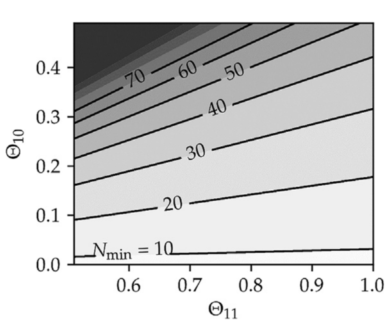

Fig. 3. Minimum number of frames N_{min} necessary for asserting that film boiling is occurring with a likelihood of 99.99% or larger, for $\varepsilon^{(0)} = 10^{-11}$.

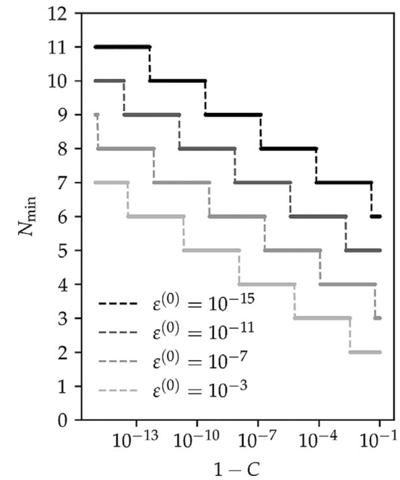

Fig. 4. Minimum number of frames N_{min} necessary for certifying that film boiling is occurring for the trained convolutional neural network ($\Theta_{11} = 0.9982$, $\Theta_{10} = 0.0018$), as a function of the detection threshold C for several priors $\varepsilon^{(0)}$.

acquired by a conventional DSLR camera at 30 Hz, corresponds to one third of a second delay.

Therefore, while the analysis presented in this section estimates the minimum number of frames necessary for detecting transition using a recursive analysis, the results are promising, particularly since, in general, it is not difficult to train a classifier to have relatively good performance metrics, i.e., $\Theta_{11} > 0.8$ and $\Theta_{10} < 0.1$, particularly during direct observation. In fact, note that the CNN presented here has near-perfect scores. Hence, these types of machine learning systems can potentially detect the transition to film boiling in a fraction of a second, which is lower than the diffusion time of many industrial temperature sensors that are used for this kind of detection.

4. Estimation of the number of frames N

While the previous section was dedicated to determining the minimum number of frames that should be expected before a prediction, in this section a more accurate prediction of the actual number of frames N necessary is performed. For instance, while the previous section assumed that the machine learning classifier correctly inferred the boiling regimes for the entire frame sequence, it is likely that they will eventually fail to infer one or multiple frames correctly. In this section, it is shown that even if the machine learning algorithm fails once every several frames, film boiling can still be detected.

For instance, note that if Θ_{11} is known, then the fraction of expected misclassifications is simply $1 - \Theta_{11} = \Theta_{01}$. Hence, while in the previous section it was assumed that the classifier always returned the correct prediction, i.e., by evaluating $L(\mathbf{X}_{i+1}) = 1$ when $T(\mathbf{X}_{i+1}) = 1$, a more precise estimation of the number of frames can be performed by assuming that a misclassification will occur approximately every $1/(1 - \Theta_{11})$ classifications.

Hence, let N_{pred} be the number of frames estimated to be necessary to detect film boiling given the classifier parameters. Naturally, as $\Theta_{11} \to 1$, then it is expected that $N_{pred} \to N_{min}$.

A new map analogous to that shown in Fig. 3 is constructed, which is now shown in Fig. 5, where the estimated number of frames N_{pred} is plotted. The classifier is forced to randomly misclassify a frame with a probability of $1 - \Theta_{11}$. Note the similarity between Fig. 5 and Fig. 3, where, for relatively low Θ_{10}, there seems to be no strong dependence on the parameter Θ_{11}. More importantly, note that even if the machine learning algorithm fails

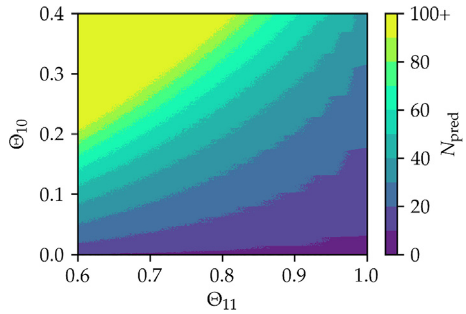

Fig. 5. Estimated number of frames N_{pred} necessary for detecting that film boiling is occurring with a likelihood of 99.99% for a prior $\varepsilon^{(0)} = 10^{-11}$ as a function of Θ_{11} and Θ_{10}.

every few frames, film boiling can still be detected within a small number of frames (i.e., in less than one second if the algorithm is bad, or at a third of a second if the algorithm is good, e.g., the CNN in Table 2).

5. Detecting the presence of film boiling

Following the previous analysis, it is important to evaluate the algorithm on real streams of film boiling data, and to allow the classifier itself to infer the boiling regimes of each frame, instead of simulating random misclassifications. Note that detecting the presence of film boiling is different from inferring the transition from nucleate to film boiling – in the former case, film boiling is continuously occurring from the beginning of the frame sequence, whereas in the latter, nucleate boiling is occurring and a transition to film boiling occurs in the frame sequence. The latter case will be discussed in Section 6. However, it should be noted that the number of frames – or time – necessary to detect the presence of film boiling sets a lower bound on the time that is expected to be necessary to detect the transition from nucleate to film boiling.

As shown in the previous section, it is expected that the number of frames N needed for detection will be no lower than N_{min} and, hopefully, close to N_{pred}. In fact, the number of frames for detection using the convolutional neural network is shown in Table 3 for direct and indirect observation, indicating the possibility of sub-second detection at 30 Hz. The results for N are averaged over 1000 randomly selected, and potentially overlapping, film boiling sequences.

A detection curve, which presents ε as a function of the frame number, is shown on Fig. 6. Note that the local reduction in ε in frame 9 is due to the misclassification of a film boiling frame. Nonetheless, the estimated likelihood that film boiling is occurring increases by orders of magnitude at each step and approaches one (100%) asymptotically, regardless of eventual misclassifications.

Despite promising results in the automatic detection of film boiling through visualization, the results were obtained from streams of consecutive film boiling frames. The possibility of detecting the transition from nucleate boiling to film boiling has still not been verified. Additionally, the film boiling sequences integrated both the test and the training set of the data used to train

Table 3
Number of frames for film boiling detection using various classifiers for $\varepsilon^{(0)} = 10^{-11}$ and C = 99.99%.

	Direct observation	Indirect observation
N	6.039	11.416
N_{min}	6	11
N_{pred}	6.020	12.014

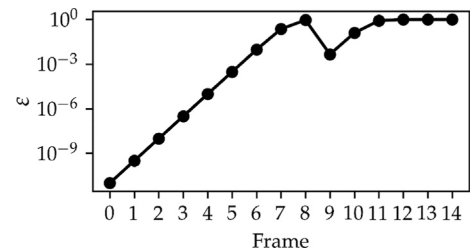

Fig. 6. Inference curve of a stream of film boiling frames during indirect observation by the convolutional neural network classifier.

the machine learning model, which may introduce bias and underestimate the true N.

6. Detecting the onset of film boiling

In this section, frame sequences of the transition from nucleate boiling to film boiling were used to understand whether the previously discussed technique is able to detect the onset to film boiling. More importantly, the methodology should not accuse a positive detection of film boiling when it is not happening, and should be able to successfully provide a positive detection once the transition occurs.

In general, two types of transition were observed when acquiring boiling data. The first is a fast and destructive transition, which lasts less than 2 s and does not encompass the entire wire, but only a small region, followed by heater failure and wire breakup. The second is a slower transition, after which stable film boiling can be observed. It should be noted that the transition frame sequences were not used to train or test any classifier. Two transition frame sequences were acquired, although only one is reported in detail in this paper for the sake of brevity.

The frame sequence is approximately 28 s long and has 856 frames. Upon careful visual examination, it was observed that the first indication of film boiling (i.e., a localized formation of a vapor film around the wire) appears between 11.5 and 12 s of the frame sequence. However, it is only at around 13 s that the wire starts emitting radiation in the visible spectrum due to the high heater temperature, and it is only at around 22 s that film boiling encompasses the entire wire. Some relevant frames of the sequence are shown in Fig. 7 in color, although note the frame is transformed to greyscale and downscaled before classification by the convolutional neural network (see Fig. 1).

The classification results as a function of time for the transition frame sequence using the trained convolutional neural network are shown in Fig. 8 for both direct and indirect observation – note that, from Fig. 7, the transition starts occurring at approximately 12 s. Nonetheless, the CNN fails to correctly infer the boiling regime two times before 12 s during indirect observation, which, if the system relied solely on the classification of a single frame, would trigger failure even when nucleate boiling is occurring – this is the type of misclassification that can be expected to happen eventually, and was thoroughly discussed in the previous sections. It should be noted that the frames in the transition sequences were not used for training, validation or test of the machine learning model. They are only used now to evaluate whether the proposed methodology can detect the onset of film boiling through visualization.

It is important to note that the Bayesian methodology proposed in this paper relies on sequential, recursive prediction. Hence, these eventual misclassifications shown in Fig. 8, particularly for indirect observation (Fig. 8b), are “filtered out”. At each misclassification the probability of an event decreases (or increases), which

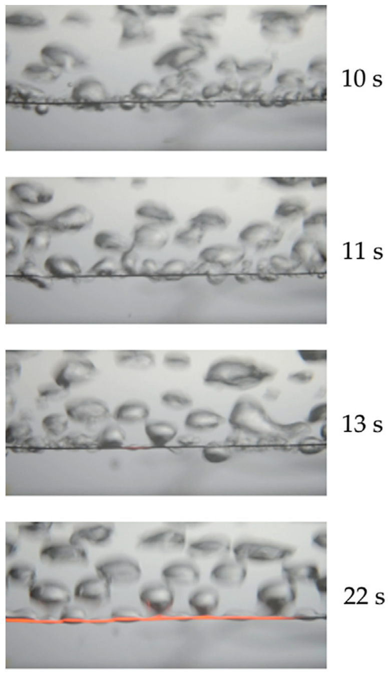

Fig. 7. Characteristic frames of Transition Sequence 1. At 10 s, nucleate boiling is occurring. At 11 s, the first indication of a vapor film formation can be detected. At 13 s clear indication of both vapor film and film boiling bubble morphology can be observed, even though the wire is still not glowing. At 22 s, the vapor film encompasses the entire wire.

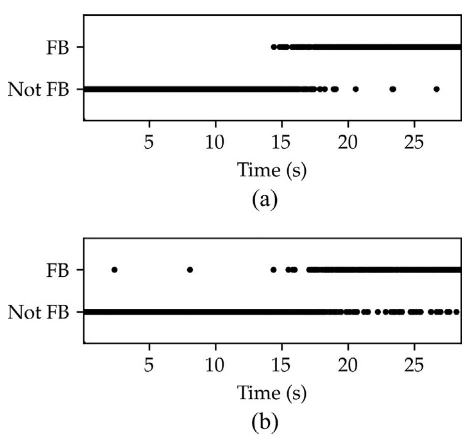

Fig. 8. Convolutional neural network classification of whether film boiling is occurring during transition from nucleate to film boiling in water in (a) direct and (b) indirect observation.

was discussed in Fig. 6, but the overall trend is not lost. Hence, note that close to the transition (i.e., starting at ~12 s), the CNN infers mixed classes given that, in fact, both nucleate and film boiling are occurring. However, as film boiling deflagrates and starts encompassing larger sections of the wire (see Fig. 7), the rate of film boiling classifications are performed by the CNN increases and becomes dominating over nucleate boiling inferences. This consecutive behavior suggests that the proposed methodology based on Bayesian statistics may work. As discussed, if the prediction were not Bayesian, the few misclassifications which can clearly be observed in Fig. 8b at around 2 and 8 s would infer failure even though film boiling is not occurring.

The detection curve—defined as ε along time—for the convolutional network over the same transition frame sequence is shown in Fig. 9. Note that, as previously discussed, it is clear that the

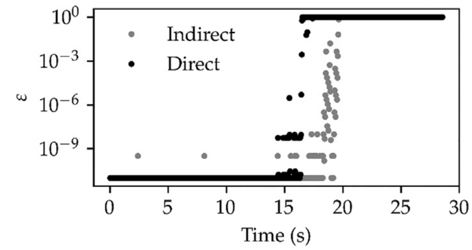

Fig. 9. Likelihood of film boiling using convolutional neural networks to feed the Bayesian estimator for $\varepsilon^{(0)} = 10^{-11}$ for direct and indirect observation.

CNN with the assistance of Bayes' law can successfully detect the transition during both direct and indirect observation. Naturally, evaluating the dependence of the detection time as a function of the initial prior $\varepsilon^{(0)}$ and the threshold C is important. Hence. the time at film boiling detection as a function of the prior $\varepsilon^{(0)}$ is then shown in Fig. 10 for several thresholds C. It is important to note that the time at detection is virtually independent of both $\varepsilon^{(0)}$ and C. This independence has been previously discussed with the assistance of Fig. 4, where it was shown that the delay due to varying thresholds and priors is possibly less than 1 s, delaying the detection by at most 10 frames.

More importantly, perhaps, is that the onset of film boiling can be detected by the proposed methodology even in indirect observation, i.e., when the wire is not visible in the visualization window, which can be inferred from Fig. 9. This is an important result, given that no information of on-wire bubble dynamics—or color—is input to the system during indirect observation. Hence, it is expected that accurate detections can be based solely on departed bubble dynamics and bubble morphology, as has already been discussed by Refs. [20,21,22].

In addition to the results presented in this section, the paper accompanies four supplementary videos, which exhibit the estimated likelihood of film boiling occurring along with the two captured sequences (i.e., the one for which the results were directly discussed in this paper, and an additional captured sequence), during both direct and indirect observation. The reader is highly encouraged to watch the videos to understand the potential of the described approach in predicting transition to film boiling, and for a better and clearer illustration of the process.

Finally, given that the onset of film boiling is at approximately 12 s, and the detection for both direct and indirect observation occurs between approximately 15–20 s, there is a 5–10 s delay in the prediction. However, it is important to put these results in perspective, given that the detection is generally before a stable vapor film encompasses the entire wire, which occurs at approximately 22 s (see Fig. 7). Additionally, it should be noted that the CNN used in this paper was trained exclusively on fully-deflagrarted film

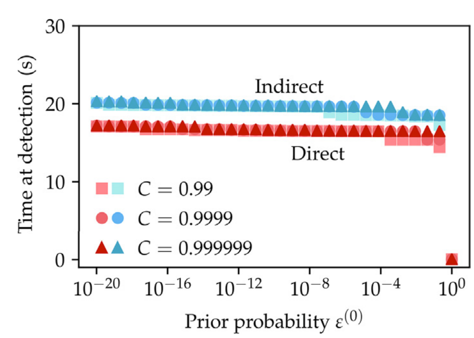

Fig. 10. Time at detection for the convolutional neural network classifier as a function of the prior $\varepsilon^{(0)}$ for various thresholds C.

boiling or nucleate boiling/natural convection frames, and not on transition frames. During the transition, both nucleate and film boiling coexist, which may confuse the classification algorithm, which in fact can be seen by the mixed classifications between 12 s and 15 s, as shown in Fig. 8.

While not directly explored in this paper, it is expected that the time for detection can be further reduced using advanced machine learning algorithms that are currently used for object detection, and not image classification, as was the case for the convolutional neural network proposed in this paper. Those algorithms can potentially detect the localized formation of a vapor layer that is characteristic of the onset of film boiling. In fact, these algorithms may be able to infer the onset of film boiling even in the wire break-up scenario, which is much faster than the situations investigated in this paper, and arguably more critical. Furthermore, even classification algorithms such as the CNN used in this paper could be used if the frame is subdivided into multiple "stripes", and a trained classifier could then be used to infer the boiling regime of each stripe, which could then be used to detect localized transitions to film boiling even when multiple regimes coexist.

Looking more closely at the site of film boiling inception shown in Fig. 11 and the supplementary videos, there is a clear pattern that distinguishes the film boiling region and the nucleate boiling region, even during the few seconds that the wire is still not glowing hot. The patterns that can be identified correspond to the creation of a film of vapor that propagates through the wire—the extent of the propagation is shown as white horizontal bars—and to the distinct bubble morphology. Hence, it is expected that if another machine learning model can detect localized transitions to film boiling—a function for which the algorithms trained in this paper was not designed—, it should be possible to achieve subsecond detection in transition, presumably even before significant temperature or resistance variations are detected by an external intrusive monitoring system. In fact, many temperature sensors such as industrial thermocouples or resistance temperature detectors possess a relatively large thermal capacity, which delays the time necessary for accurate temperature sensing.

Therefore, while the results described in this paper are certainly promising, there is significant room for improvement regarding the detection of the transition to film boiling using low speed visualization and machine learning, particularly with respect to time to detection. Additionally, a setback of the analysis presented thus far is the necessity of operating a heat transfer device at failure in order to acquire information about the classifier performance on failure. It is expected that this problem can be overcome—or at least minimized—by the design of machine learning systems specifically tailored for outlier detection, where a classifier (such as a convolutional neural network) is trained solely on regular system operating conditions, and automatically detects whenever it departs from normal operation.

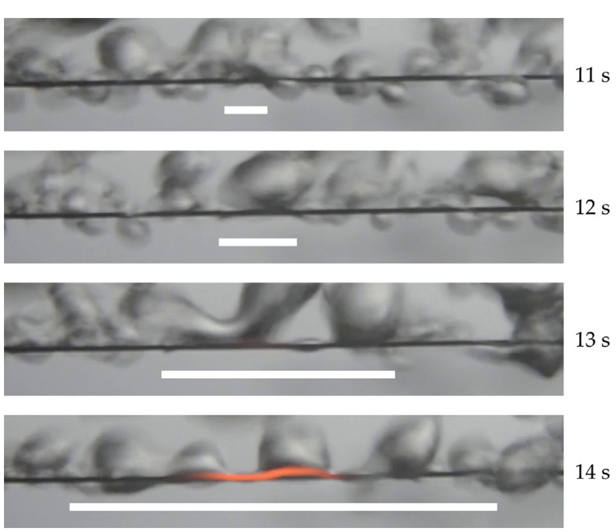

Fig. 11. Wire observation of the transition from nucleate to film boiling. White bars indicate the extent of the transition. The region does not represent the entire wire.

7. Conclusion

In this paper, it was shown that a convolutional neural network (CNN) can be trained to classify boiling regimes with over 99% accuracy from visualization data, even when the heater is not in the visualization window, corroborating the results of Ref. [21]. Then, the CNN is used in conjunction with Bayesian inference to accurately detect the onset of film boiling. It is shown that the number of frames necessary for detecting the onset of film boiling is generally low, possibly lower than 10 frames, which, when operating with a conventional, low resolution, low speed camera at 30 Hz, corresponds to sub-section detection of film boiling, potentially faster than measurements made by temperature sensors with relatively large thermal capacity.

Finally, an additional and natural next step following up on the results presented in this paper is the development of a real-time film boiling detection system, which should be capable of acquiring, processing, classifying and detecting in real-time. Given the increasingly high processing power of miniaturized hardware, this should be a viable task even with current technology, and would help further demonstrate the potential for machine learning application in multiphase flow systems.

Conflict of interests

No conflict of interests are present.

Acknowledgements

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Appendix A. Supplementary material

This paper accompanies four supplementary videos, regarding direct and indirect observation of two frame sequences that capture the transition from nucleate to film boiling. The prior is assumed to be $\varepsilon^{(0)} = 10^{-11}$ and the detection threshold $C = 0.9999$. The slidebar depicts the likelihood of film boiling as estimated by the proposed Bayesian inference in logarithmic. The video is overlaid in red when film boiling is detected with a likelihood of 99.99%. Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ijheatmasstransfer.2018.12.070.

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