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Mohammad Autif Shahdhaar
   Indian Institute of Technology Bombay

Arpan Srivastava
   Nirma University

Atul Srivastava
   Indian Institute of Technology Bombay

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Machine learning aided investigation of dynamics of immiscible droplet impingement on liquid pools: A study across varying pool depths and droplet viscosities

Mohammad Autif Shahdhaar¹, Arpan Srivastava², Atul Srivastava³,*

¹Center for Research in Nano Technology and Science, Indian Institute of Technology Bombay, Mumbai, India – 400076
²Department of Electronics and Communication, Institute of Technology, Nirma University, Ahmedabad, India – 382481
³Department of Mechanical Engineering, Indian Institute of Technology Bombay, Mumbai, India – 400076

*Corresponding author: atulsr@iitb.ac.in

ABSTRACT

The interactions of an immiscible droplet impinging on liquid pools bear significant implications across a wide array of applications, as well as in natural phenomena. In this paper, the dynamics associated with an immiscible droplet impinging on a liquid pool/film of varying depths have been elucidated. The study encompasses the impact of silicone oil droplets of four different viscosities (1, 10, 100, and 1000 cSt) upon a water pool of three non-dimensional pool heights $h^* = 1, 2.5, \text{ and } 5$. The phenomenon of droplet impact at two Weber numbers ($We = 50$ and 100) is captured through high-speed videography. The dynamics of impingement, associated with the immiscible liquid combination, are delineated by employing Mask R-CNN machine learning (ML) model. ML model generated masks are used to ascertain the dynamics of various cavity parameter. Further insights into the phenomena have been developed through a detailed energy analysis carried out pre- and post-impact. The performance of ML model is compared with the manually annotated images, exhibiting impressive level of agreement. Results reveal that during the cavity formation phase, low viscosity droplets conform to the cavity shape during their descend into the pool. In contrast, high viscosity droplets maintain their shape during cavity formation, showing pinning at the oil-water interface. Energy analysis shows better energy transfer from droplet to the cavity for low viscosity droplets (> 90%), while less than 50% of the impact energy is transferred for higher viscosity droplets. This study is among the first to apply machine learning to this complex fluid phenomenon, offering insights into the physics and potential applications in multiphase flows.

Keywords: Drop on pool, Immiscible droplet impact, Machine Learning, Cavity dynamics

I. Introduction

Flow visualization plays a pivotal role in understanding the underlying physics of fluid flows and associated phenomena, making it an essential tool across diverse scientific and
engineering disciplines. Various methods, ranging from classic dye injection (Reynolds 1883) to particle image velocimetry (PIV) (Adrian 1991; Grant 1997), have been developed to visualize flows and gain insights into their behavior. The advent of high-speed imaging, coupled with the state-of-the-art computational resources, that allow huge data storage and fast processing speeds, have brought about a paradigm shift in flow visualization allowing for the capture of intricate dynamics of rapid phenomena, such as droplet impact, shockwaves and two-phase flows (Chen and Liang 2008; Thoroddsen et al. 2018; Sinha and Srivastava 2020). Scales of temporal and spatial resolution offered by the present generation of flow visualization techniques is phenomenal, which makes them one of the most preferred tools to investigate even some of the complex flow features associated with phenomenon under study. Among the large range of application areas of these experimental techniques, the phenomenon of droplet impact of liquid pool(s) of varying dimensions has drawn considerable attention of researchers in recent times. Phenomenon includes varying length as well as time scales, along with complex dynamics of the various interfaces that continually evolve with time upon the droplet impact on the liquid pool (Yarin et al. 2017).

Interaction of droplet with liquid films and pools is observed frequently in the nature as well as in the commercial applications (Parry et al. 2018; Hack et al. 2018; Park et al. 2020). These interactions are governed by several parameters, such as the pool or film thickness, the droplet size and velocity, and the physical properties of the fluids involved. Miscibility of droplet and pool liquid is also an important factor, dictating the behavior following the droplet impingement. The droplet is absorbed into the liquid pool for miscible pool-droplet liquid combination. However, in case of immiscible pool-droplet liquid combination, additional forces, viz buoyancy and interfacial surface tension, affect the flow dynamics and the droplet forms a (ball) lens over the liquid pool after attaining the sessile state. Given the multitude of factors involved, a combination of different phenomena can be observed for varying Weber and Froude numbers. These phenomena include coalescence, cavity formation, bubble entrapment, Worthington jet, and capillary waves.

The phenomena of droplet impingement on liquid pool/film have been studied extensively over the years (Rein 1993; Weiss and Yarin 1999; Rioboo et al. 2003; Agbaglah and Deegan 2014) due to its high degree of prevalence in nature and technological implications in various domains. At the moment of impact, anytime droplet possesses two forms of energy: kinetic energy and surface energy. When the Weber number is high, the kinetic energy of the droplet is significantly larger, causing it to behave like a solid sphere and penetrate the interface.
into the pool (Yarin et al. 2017). The impingement of droplets at high Weber numbers is associated with several phenomena resulting from hydrodynamic instabilities in the liquid pool, which are caused by the high kinetic energy of the droplet. Depending on the magnitude of the Weber number, post-impact observations may include the formation of a crater due to droplet penetration, the entrapment of air bubbles, the formation of a crown, and the ejection of a secondary central jet, referred to as a Worthington jet (Berberović et al. 2009). The impact phenomenon of an interacting droplet on a liquid pool is determined by the non-dimensional pool height \(h^* = h_p/D_0\) and can be classified into three regimes: thin film \((h^* < 1.5)\), shallow pool \((1.5 < h^* < 4)\), and deep pool \((h^* > 4)\) (Tropea and Marengo 1999). The dynamics for each regime are dictated by the substrate roughness, pool depth, and gravity, respectively.

Different phenomena within the liquid pool close to the area of impact, which correspond to various impact regimes, have been visualized and examined. Cavity dynamics and bubble entrapment mechanisms, along with the diverse regimes for droplet-pool interaction, have been outlined by Oguz and Prosperetti in their established theoretical model (Oguz and Prosperetti 1990). Bisighini et al. proposed a theoretical model of crater dynamics for high Weber and Froude numbers and estimated the evolution of crater depth with time (Bisighini et al. 2010). A simulation study to investigate the impact of droplets on a liquid pool at different ranges of Weber numbers and Froude numbers were conducted by Ray et al. (Ray et al. 2015) Different regimes of coalescence, jet formation, and crater characteristics based on the Weber and Froude numbers were identified. The mechanism of crater collapse and formation of Worthington jet was reported in detail by Thoroddsen et al (Thoroddsen et al. 2018). Ersoy and Eslamian (Ersoy and Eslamian 2019) conducted an experimental study to investigate the mixing characteristics of dyed water droplets impinging on a water film for different Weber numbers and pool depths. Different mixing mechanisms such as turbulence, hydrodynamic instabilities, capillary waves, and molecular diffusion were identified.

While the majority of reports have focused on miscible droplet-pool liquid combinations, recent studies have shifted their attention to understanding the dynamics of immiscible drop-on-pool configurations (Jain et al. 2019; Roy et al. 2022; Minami and Hasegawa 2022; Wang et al. 2023). Jain et al. studied the crater dynamics for high Weber number oil droplet of different viscosities impinging on deep water pool (Jain et al. 2019). The study indicated that the depth of the crater was influenced by both the viscosity of the droplet and the inertia of the pool liquid. Additionally, crown formation with fingering projections at the rim, resulting from crown-splash instability, were also observed. Roy et al. (Roy et al. 2022)
mapped the hydrodynamics of the thin air film entrapped between the impinging water droplet and the oil pool at the time of impact. Minami and Hasegawa (Minami and Hasegawa 2022) conducted a series of experiments with various miscibility combinations of droplet and pool liquid. They illustrated the effect of drop solubility on the crater and jet formation, and carried out energy analysis for the pre and post impact. A recent study by Feng et al. (Wang et al. 2023) investigated the impact and freezing of hexadecane droplet on cooled water pool. Based on the temperature of the liquid pool, three phases viz. jet, flat and bowl phase, were observed, which were attributed to the onset of solidification process of the droplet liquid.

Flow visualization through high-speed optical imaging system has played a major role in the investigation of a droplet impingement phenomena (Ersoy and Eslamian 2020; Singh and Kumar 2022) as it provides insight into the dynamics of the phenomena with high temporal resolution without disrupting the process. To study the dynamics following the droplet impingement on liquid pool and quantify the physical quantities of interest, the images captured through high-speed imaging need to be analyzed and processed accordingly. High-speed imaging generates a large amount of temporally resolved data (in the form of images), which must be analyzed to extract the physical quantities of interest. However, manual analysis of such a large data set is a labor-intensive and time-consuming task that is also quite prone to human error. In this regard, various algorithms are available in the literature, which generally follow a standard approach of image preprocessing, including techniques such as contrast enhancement and noise removal. This is followed by the manual identification of the region of interest, and then image segmentation and tracking of useful components. However, in certain cases, these algorithms are not effective, such as in cases where there is an abrupt contrast change from one frame to another or in cases where the object boundaries are not that sharp (due to exposure, resolution limitation or curvature of interface or meniscus formation). In such cases, the conventionally employed image processing algorithms show serious limitations as they turn out to be inconsistent and require considerable manual efforts to remove their irregularities from the data.

Machine learning (ML) offers plausible solutions to these challenges associated with the conventional image processing approaches by automatically extract meaningful features from the flow visualization images, without the intrinsic shortcomings associated with conventional image processing. It providing reliable and accurate results without the need for manual adjustment at each step once the ML model has been trained. By virtue of these traits, machine learning approaches, to the maximum possible extent, avoid these inherent
uncertainties that may creep in due to human/manual intervention, make the analysis much faster and hence reduce the time required for processing even the voluminous experimental data set. Recent advances in Machine Learning (ML) and Convolutional Neural Networks (CNNs) have enabled the development of automated image processing techniques for image segmentation, object tracking, and detection (Redmon et al. 2016; He et al. 2017). These techniques are particularly applicable in the study of multiphase flows, where the application of CNNs has been demonstrated in various studies (Hobold and da Silva 2019; Liu et al. 2022; Soibam et al. 2023). CNNs offer the ability to extract spatial information for different phases and detect gas-liquid interfaces, providing valuable insights into the dynamics of multiphase flows (Rutkowski et al. 2022; Tai et al. 2022; Sibirtsev et al. 2023).

Based on the literature review, it is clear that the interactions of droplets with liquid pools and films are of significant importance and understanding the dynamics and underlying mechanisms of these interactions is crucial for enhancing their applicability and efficacy in a wide range of scenarios. However, there is a scarcity of studies on the impingement of immiscible drops on liquid pools and films at low Weber numbers. Low Weber number impacts are crucial, exhibiting a variety of drop-pool interactions, including partial and full coalescence, droplet cascading, droplet entrainment, and secondary jet formation. The studies in this regard are also limited by challenges one faces while handling the voluminous data that need to be processed to delineate the dynamics associated with droplet impact. Moreover, studies pertaining to application of machine learning/deep learning algorithms to characterize the droplet impact phenomena and the resultant dynamics of various interactions are highly scarce. With this as the motivation and in an effort to bridge these gaps, this paper investigates the impingement dynamics near the region of impact for different grades of silicon oil (with viscosities of 1, 10, 100, and 1000 cSt) on water pools and films (with thicknesses $h^* = 1, 2.5, \text{ and } 5$). The study employs R-CNN machine learning algorithm (He et al. 2017) to successfully track interfaces post-impact at Weber numbers 50 and 100, thereby revealing the cavity dynamics and facilitating a detailed energy analysis. The ML model was trained using a set of 540 manually annotated images, captured at various time instants during the impingement phenomenon. The trained model was subsequently utilized to track the cavity and air-water interface for the experimental data. The cavity dynamics derived from the model were validated against manually annotated images, demonstrating a reasonable agreement between the two datasets.

II. Experimental Setup
Experiments have been conducted for silicon oil droplets, having different viscosities, impinging on a water pool of varying depths. The details of the experimental setup have been shown schematically in Fig. 1. The setup consists of a droplet dispenser (Holmarc) which is connected to a stainless-steel needle of outer diameter of 1.24 ± 0.02 mm and having a blunt tip. The needle is attached to a laboratory stand which is mounted on a lab jack (Holmarc). This allows the needle to traverse vertically and release the droplet at different heights \( h \). The velocity of the droplet \( U = \sqrt{2gh} \) is calculated by assuming free fall under the acceleration due to gravity \( g \) as the drag force on the droplet is not significant at these low velocities. The silicone oil droplet detaching from the needle under the influence of its own weight, impinges the water pool of different heights maintained in a test section (80×80×25 mm\(^3\)) placed under the needle. The test cell is made of PMMA (polymethyl methacrylate) acrylic sheet in order to provide optical access for flow visualization. A diffuse light source (Phlox, 40W, color 5700K) is placed parallel to the test cell (see Fig. 1) for visualizing the droplet impact and cavity formation post impact. The phenomenon of droplet impingement is captured through a high-speed camera (Phantom VEO 440) at a frame rate of 2000 fps with a resolution: 1280×1100 pixels, which is connected to a computer used to trigger and save the data from the high-speed camera.

The experimental setup, shown in Fig. 1, is placed on a vibration suppressing pneumatic table. The experiments have been conducted at room temperature (25±1°C) and a relative humidity of 45-50 %. In the present study, four different grades of silicone oil, having
viscosities $\nu = 1, 10, 100$ and $1000$ cSt, were used as the fluid for the impinging droplet. The diameter ($D_0$) of the droplet has been calculated optically through image processing. The test section is filled with deionized (DI) water of different pool heights ($h_p$) for the present experiment. The pool heights for each grade of silicone oil are chosen such that the non-dimensional pool height $h^* = \frac{h_p}{D_0}$ are 1, 2.5 and 5, which correspond to thin film, shallow pool and deep pool regime, respectively. The properties of the interacting fluids are given in Table 1.

<table>
<thead>
<tr>
<th>Fluid</th>
<th>Density $\rho$ (kg/m$^3$)</th>
<th>Viscosity $\mu$ (mPa-s)</th>
<th>Surface tension $\gamma_D$ (mN/m$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>997</td>
<td>0.89</td>
<td>71.78</td>
</tr>
<tr>
<td>Silicon oil (1 cSt)</td>
<td>762</td>
<td>0.76</td>
<td>16.89</td>
</tr>
<tr>
<td>Silicon oil (10 cSt)</td>
<td>938.25</td>
<td>9.38</td>
<td>21.66</td>
</tr>
<tr>
<td>Silicon oil (100 cSt)</td>
<td>956.17</td>
<td>95.62</td>
<td>21.01</td>
</tr>
<tr>
<td>Silicon oil (1000 cSt)</td>
<td>986.67</td>
<td>986.67</td>
<td>22.44</td>
</tr>
</tbody>
</table>

The experiments have been conducted at different velocities to arrive at two Weber numbers $We = 50$ and $We = 100$ for all grades of silicone oil. The details of the droplets and impingement parameters at different grades of silicone oil at each pool height are given in Table 2.

### III. Methodology

Mask R-CNN (Mask Region-based Convolutional Neural Network) is a deep learning model for object segmentation. It extends the scope of the Faster R-CNN object detection model (Ren et al. 2015) which in itself is an evolution of the original R-CNN (Region-based...
Convolutional Neural Network) architecture (Girshick et al. 2013). Mask R-CNN, was first proposed by He et al. (He et al. 2017) which significantly improved the task of object detection by not only providing the bounding boxes for the objects but also pixel-wise masks for each object instance within an image. Mask R-CNN has consistently showed its capability for various computer vision tasks, particularly in the field of object instance segmentation. Given the capabilities of this model, the present study employs Mask R-CNN to a novel and challenging task of interface tracking within liquids, which requires the accurate detection and segmentation of interfaces between different interacting fluid media. The architecture of Mask R-CNN deep learning model is shown in Fig. 2. It consists of a backbone network, region proposal network (RPN), classifier and prediction modules.

Fig. 2. Architecture of Mask R-CNN model

The backbone network is the first and foundational part of an object detection model. It is responsible for extracting meaningful features from the input image. These features provide different levels of abstraction, from low-level details to high-level semantics. These networks typically consist of convolutional layers based on architectures like VGGNet (Visual Geometry Group) (Simonyan and Zisserman 2014), ResNet (Residual Network) (He et al. 2016), FPN (Feature Pyramid Network) (Lin et al. 2016) etc. Many backbone networks are pre-trained on large datasets like ImageNet, which contain a vast array of images from various categories. Pre-training helps capture general visual features, making these networks useful as starting points for a wide range of tasks. In the present study, ResFPN (Residual Skip Connections in Multi-Resolution Feature Pyramid Networks) (Rishav et al. 2020) is employed as the backbone architecture. This choice allowed effective capturing of a comprehensive range of features that encompass the intricate interfaces within the liquid pool across multiple
resolutions. The choice of backbone can significantly impact the model's performance, as deeper and more complex backbones can capture richer features.

The core of Faster R-CNN that sets it apart from many other object detection models is the Region Proposal Network (RPN). Its primary function is to propose candidate regions in an input image that are likely to contain objects of interest. RPN utilizes the feature maps generated by the backbone network to establish anchor points. Taking these points as center anchor boxes of different lengths and aspect ratios are defined. RPN then slides a small convolutional window (of 1×1 or 3×3 pixels, as depicted in the RPN box in Fig. 2) over each spatial location in the feature maps. At each location, the network predicts two values for each anchor box, viz, object probability (also called as object score) and regression offsets. Object probability quantifies the likelihood that the content enclosed within the bounding box represents a foreground object rather than background noise. In the present set of images, it specifically pertains to determining the probability that the enclosed content corresponds to the liquid interface, which is the focal point of our analysis. Regression offsets are used to refine the position and size of the anchor box to better align with the true object boundaries.

RoI (region of interest) Align is a technique that addresses the spatial quantization problem when extracting features from RoIs of the images that needs to be analyzed. RoI align takes the region of interest as input and divides it into a grid of smaller cells (e.g., a 2×2 or 3×3 grid). For each cell in the grid, it performs bilinear interpolation on the original feature map. This means that it calculates the weighted average of the feature map values at the non-integer coordinates within the cell. This interpolation process produces a more precise representation of the feature values in the RoI. The feature values obtained from each cell are then concatenated to form a feature vector that accurately represents the information within the RoI.

Following the classification of features of the input image, the model identifies the interfacial shape (see Fig. 2). In this regards, Mask Head is a critical component of Mask R-CNN architecture to predict and identify the interfacial shape. It is an addition to Faster-RCNN which is designed for object instance segmentation. Its primary function is to generate pixel-wise masks that delineate the exact boundaries of individual object instances within an image. It takes the input as ROIs generated and aligned in RPN which represent candidate regions where objects may be present. It's typically a small neural network, which consists of convolutional layers, up-sampling layers, and activation functions. Mask Head then predicts a binary mask for each RoI, where each pixel within the mask is classified as either belonging to
the object instance or not. In the context of this study, it precisely discerns the interfaces present within the image and forms a binary mask for each image. These binary masks serve as high-resolution representations highlighting the exact boundaries of the liquid interfaces under scrutiny. This is done by applying a sigmoid activation function at the output of the network for each pixel, making the prediction for that pixel binary. These masks are combined with the bounding box information to produce precise object instance segmentations.

Mask R-CNN employs a multi-task loss function for training:

- **Classification Loss**: Its primary purpose is to enable object classification, specifically in our context, where it involves determining whether the content within the region of interest constitutes an interface between liquids or not.

- **Bounding Box Regression Loss**: This loss also plays an important role in object detection and segmentation. Its purpose is to refine the coordinates of the bounding boxes predicted by the model. Initially the bounding box provided by the model may not be perfectly aligned with the actual object boundaries, thus it measures the disparity between the predicted bounding box coordinates and the ground-truth bounding box coordinates for the objects within the RoIs. Minimizing this loss leads to more accurate object localization.

- **Mask Loss**: It is a crucial part of the multi-task loss function in Mask R-CNN, specifically addressing the instance segmentation aspect of the model. In interface tracking tasks, the goal is to segment and track the boundaries or interfaces between different substances or phases, within a liquid medium. These interfaces can be intricate and dynamic, making their precise identification challenging. To address this, mask loss function is defined that quantifies the dissimilarity between the predicted binary masks and the ground truth masks. Ground truth masks are used as the target or reference for training the model. In the training phase parameters of the model get continuously adjusted in order to minimize this loss function. This process guides the model to generate more accurate binary masks for the interfaces.

### A. Training of the model

A diverse dataset consisting of more than 500 images of size 1280 x 1100 pixels were collected. These images encompass a wide range of time instances in cavity formation post impact for different cases of droplet viscosities and pool heights. Before training the model, each image was meticulously annotated using an open-source annotation tool. It involves marking the precise locations and boundaries of objects of interest within the images. After
ensuring that the dataset is properly labeled, the training environment, including hardware resources and software dependencies was setup, to accommodate the computational demands of deep learning model. The entire training was carried out on a system which uses $2 \times$ single-core hyperthreaded Xeon Processor @ 2.3Ghz with 128 GB of RAM and Quadro P400 as GPU accelerator. In order to optimize the model's training process, the hyperparameters were tuned. The model was then trained on a total of 110 epochs. During each epoch, the model iteratively processed the entire dataset, adjusting its internal parameters to minimize the chosen loss functions. After the training phase, the model achieved a remarkable accuracy rate of approximately 94% on the validation dataset. Finally, the model was prepared for deployment, enabling it to make real-time predictions on new, unseen images.

As a representative case to demonstrate the implementation of the Mask R-CNN ML model, Fig. 3 shows the interface tracking and mask generation from the testing dataset images. These results vividly demonstrate the model's impressive accuracy in predicting the interface (highlighted in blue) and also generating its precise binary mask.

![Interface Tracking and Mask Generation](image)

**Fig. 3.** Interface tracking and mask generation during the impingement of a droplet on a liquid pool using Mask R-CNN model

### IV. Results and discussion

#### A. Validation of the model

The cavity dynamics for the silicone oil droplet impinging on a liquid pool are quantified by employing R-CNN machine learning model. In order to assess the performance and validate the current model, a comparison is drawn between the parameters of interest
obtained through the model and manually annotated masks for the image sequence obtained through high-speed imaging. The present approach for machine learning model validation is similar to that followed by Soibam et al. (Soibam et al. 2023). The comparison is made for six different cases with varying pool height and Weber number (see Fig. 4 and Fig. 5).

Fig. 4 shows the results of the model performance in tracking the cavity at different time instants against that of the manually identified masks. The difference between the temporal variation of the cavity parameters obtained through the model and the manual annotations is limited to a maximum of 15%, as seen in Fig. 4. Relatively higher magnitude of difference is observed for the average cavity diameter [Fig. 4 (a)], while the model tracks the cavity depth with better accuracy [Fig. 4 (b)]. This can be due to the fact that the errors are accumulated while calculating the average diameter (see Section IV-B).

Fig. 5 depicts the comparison of maximum cavity depth and average diameter based on the present machine learning model and manually masked images. It is worth noting that both the parameters, the maximum cavity diameter and maximum cavity depth, retrieved through both the approaches show a reasonably good agreement. In these cases, the differences between the values are under 6%. The maximum error in estimating the maximum cavity depth and average cavity diameter was 3.73% and 5.51%, respectively. For $h^* = 1$, the maximum cavity depths coincide for all cases as the cavity expansion is limited by the bottom plate of the pool [Fig. 5 (b)].

The above discussion highlights the effectiveness of the R-CNN ML model in tracking the interface and enabling the extraction of the cavity parameters from the images and
eliminating the need for manual intervention. The model can be automated, thereby facilitating the processing of voluminous datasets (of images) within a significantly reduced timeframe, and mitigating the potential for human errors that are inherently associated with manual masking. Additionally, the model allows for a more detailed analysis of the cavity dynamics, as it does not rely on assumptions pertaining to the cavity shape, a limitation that has been observed in previous studies.

B. Cavity Dynamics

As the droplet impinges the air-water interface, it plunges into the liquid pool, forming a cavity in the liquid pool that evolves with time from the point of impact. Fig. 6 and Fig. 7 depict the time evolution of the phenomenon of impingement of silicone oil droplet (of different viscosities) and Weber numbers on a liquid pool of various heights. Images shown are time lapsed and belong to a large dataset recorded through high-speed videography (see movie files in the supplementary material). It can be noted from Fig. 6 (a) that the phenomenon of secondary jet formation, subsequent to the collapse of the cavity, is observed in case of low-viscosity droplet impact. On the other hand, droplets characterized by higher viscosities exhibit a notable retention of their original shape during the cavity formation, as can be observed in Fig. 6 (d) and Fig. 7 (b). For droplet impacts with low Weber number ($\text{We} = 50$), the droplet may bounce back after the collapse of the cavity at the higher viscosity levels [see Fig. 7 and corresponding movie files in supplementary material]. In order to characterize the cavity
As stated in the previous section, the masks generated from the ML model enable a more intricate and faster analysis of the cavity dynamics as the assumptions pertaining to the cavity shapes at different time instants, that are generally associated with other conventional...
approaches, are omitted. Various studies in the open literature, estimate the volume of the cavity by assuming it to be of hemispherical or cylindrical shape at a particular time instant. However, this assumption may not be valid for all time instants of cavity evolution as the cavity shape does not always confer to these assumed geometric shapes, which can be clearly seen from Fig. 6 and Fig. 7. Consequently, the data obtained through this method will invariably contain some degree of error due to these assumptions. In contrast, the present study employs the machine learning algorithm to track the interfaces during the cavity formation and receding, and generate masks conforming to the shape of the cavity at each time instant. These masks generated through the ML algorithm are used to calculate the parameters such as volume, average cavity diameter and cavity depth with greater accuracy. These images of the masks are analyzed through MATLAB. Each row of the mask indicates the diameter, $D_i$ (in pixels) at that horizontal plane. The average cavity diameter, $D_c$ is calculated by taking an average of the diameters of the various horizontal planes consisting the whole mask. The volume calculation method employed here still inherits the axisymmetric assumption, similar to previous studies. Thus, the diameter at each horizontal plane is assumed to be a disk of area $A = \frac{\pi}{4} D_i^2$ and of thickness equivalent to the physical length corresponding to 1 pixel. These area values are summed to obtain the volume of the cavity. Following this, the volume of the cavity ($V_c$) is computed using Equation 1.

$$V_c = \sum_{i=1}^{n} \frac{\pi}{4} D_i^2$$

Fig. 8 shows the variation of maximum cavity diameter and normalized cavity diameter for an oil droplet of different viscosities impinging on water pool of various depths. It can be observed that larger cavity diameter, for all pool heights, is associated with impinging droplets at higher Weber number ($We = 100$). The viscosity of the droplet also plays a role in determining the cavity diameter. The cavity attains the maximum average diameter after it starts collapsing, as can be seen from Fig. 4 and Fig. 6. In case of silicon oil of 1 cSt viscosity, during cavity formation phase, the droplet conforms to the shape of the cavity as it plunges into the liquid pool. As the cavity enters the receding phase, the oil droplet in the cavity deforms readily under the action of buoyancy and surface tension due to its low viscosity. This causes a collapsing cone-like shape of the receding cavity, resulting in a lower average diameter. For oil droplets of viscosity 100 and 1000 cSt, the impinging droplet does not undergo any significant deformation during its impact at these Weber numbers due to the high viscosity [see
The droplet retains its shape, and thus, doesn’t spread at the bottom of the cavity. This is accompanied by pinning of the oil-water interface around the droplet, which further prevents any expansion of cavity during the receding phase. However, oil droplets of 10 cSt viscosity show a different cavity behavior upon impact. It should be noted that the average cavity diameter is consistently larger for silicone oil of 10 cSt viscosity for all cases (Fig. 8). The viscosity of the silicone oil (10cST) allows the droplet to deform at the impact, but resist the deformation once the cavity starts to recede. This results in a wider cone formation, and thus, a larger cavity diameter as the cavity recedes.

The variation of maximum cavity depth and normalized cavity depth for an oil droplet of different viscosities impinging on water pool of various depths is depicted in Fig. 9. The droplet with a higher Weber number results in a deeper cavity, due to its higher kinetic energy. Fig. 9 reveals that the cavity depth, on the whole, increases with increase in the pool height.
while there is no clear dependence on the viscosity of the droplet liquid for Weber number, $We = 100$. On the other hand, the pool height and droplet viscosity seem to have a significant effect on the cavity depth at $We = 50$. It can be attributed to the fact that the impact timescale for low Weber number impacts is larger (Yarin et al. 2017). Due to this, the droplet at low Weber number and the pool interface have a larger time to interact compared to higher Weber number droplet and thus, deform accordingly. In contrast, the droplets at Weber number $We = 100$ act as solid spheres and plunge into the liquid pool. It is worth noting that the cavity depth is more or less similar for all cases at $h^* = 1$, as the maximum achievable cavity depth (created due to the droplet impingement) is limited by the pool depth. However, the droplet has higher energy for $We = 100$ and in order to dissipate the extra energy, the corresponding maximum cavity diameter for $We = 100$ is larger, as can be seen from Fig. 8.
**Energy Analysis**

In order to further understand the dynamics associated with the droplet impingement on a liquid pool, energy analysis is carried out pre and post its impact on the liquid pool. Prior to the impact, kinetic energy \( E_{ke(D)} \) and surface energy \( E_{s(D)} \) are associated with the droplet. These energies, when combined, represent the total impact energy \( E_{im} \) of the droplet upon impact, as follows:

\[
E_{im} = E_{ke(D)} + E_{s(D)} \quad (2)
\]

The kinetic energy \( E_{ke(D)} \) and surface energy \( E_{s(D)} \) of the impinging droplet can be defined as:

\[
E_{ke(D)} = \frac{1}{2} \rho_D V_D U^2 \quad (3)
\]

\[
E_{s(D)} = \pi D_0^2 \gamma_D \quad (4)
\]

where, \( \rho_D \) and \( \gamma_D \) are the density and surface tension of the oil droplet, respectively.

Upon impact, the energy associated with the droplet is transferred to the liquid pool through interface deformation, capillary waves and viscous dissipation. The interface deformation that results in cavity formation has three types of energies associated with it, viz, cavity surface energy \( E_{s(c)} \), wave swell energy \( E_{w(c)} \) and cavity potential energy \( E_{pe(c)} \).

These energy terms are defined as follows (Minami and Hasegawa 2022):

\[
E_{s(c)} = \frac{\pi}{2} D_c^2 \gamma_p \quad (5)
\]

\[
E_{w(c)} = \frac{\pi g \rho_p R_c^4}{36} \quad (6)
\]

\[
E_{pe(c)} = \rho_p V_c g H_g \quad (7)
\]

where, \( \rho_p \) and \( \gamma_p \) represent the density and surface tension of the water pool, respectively. \( R_c \) and \( H_g \) are the maximum average radius and distance of center of gravity of the cavity from the pool interface, respectively. Thus, the total energy of the cavity \( E_c \) can be given as:

\[
E_c = E_{s(c)} + E_{w(c)} + E_{pe(c)} = \frac{\pi}{2} D_c^2 \gamma_p + \frac{\pi g \rho_p R_c^4}{36} + \rho_p V_c g H_g \quad (8)
\]
Based on the above equations, the maximum cavity energy and the normalized cavity energy for impinging droplets of varying viscosities and pool depths have been shown in Fig. 10. The plots show that the cavity energy is higher for larger Weber number ($We = 100$). However, normalizing the cavity energy with the initial impact energy reveals that the energy transfer from droplet to the cavity is better at lower Weber number ($We = 50$). Low Weber number droplets have more time for interfacial interaction compared to the droplets impacting at larger Weber number. This results in the release of surface energy through development of three-phase contact lines and thus, better energy transfer. It should also be noted that at higher Weber number, the droplet plunges into the liquid pool, which leads to the development of capillary waves of larger amplitude (Shahdhaar et al. 2022). In addition to this, stronger wake vortices and higher viscous dissipation in the liquid pool can also be expected for higher Weber number droplet impacts. It is also seen that normalized cavity energy decreases with increasing viscosity of the impinging droplet. In the case of silicone oils of 100 and 1000 cSt viscosity, less than half the impact energy (44.3% for $We = 50$ and 42.1% for $We = 100$) is transferred to
the cavity. This can be attributed to the lower cavity diameters observed at these droplet viscosities. This behavior at viscosities of 100 and 1000 cSt can also be attributed to the pinning of contact lines [Fig. 6 (d)], and in some cases, the droplet bounce-back and eject from the cavity as the cavity recedes [see supplementary movie file corresponding to Fig. 7]. It should be noted that lower viscosity oil droplets transmit the droplet energy efficiently to the cavity (as high as 94% for \( \text{We} = 50 \) and \( h^* = 5 \)). The liquid pool height also plays a part in determining the extent of energy transfer from the droplet to the cavity, with thin film \( (h^* = 1) \) exhibiting the lowest while the deep pool \( (h^* = 5) \) showing the highest cavity energy. The maximum cavity energy is observed for the case of 10 cSt silicone oil droplet impinging at \( \text{We} = 100 \) on a deep pool \( (h^* = 5) \).

V. Conclusion

The present study focused on investigating the dynamics of immiscible silicone oil droplet impacting on a liquid pool of varying depths, and successfully highlighted the application of machine learning model to extract the post-impact cavity dynamics from a sequence of high-speed images. To this end, droplets of four different grades of silicone oil, based on different viscosities of 1, 10, 100, and 1000 cSt, impinged on a water pool of three non-dimensional pool heights \( h^* = 1 \), 2.5, and 5. The phenomenon of droplet impact was observed at two Weber numbers \( \text{We} = 50 \) and 100. Mask R-CNN machine learning model was utilized to outline the dynamics of the impingement and carry out the energy analysis pre and post impact. The performance of the ML model was compared with the manually annotated images and showed a remarkable level of agreement. The results indicated that during the cavity formation phase, droplets at low viscosities (1 and 10 cSt) conform to the shape of the cavity as they descend into the liquid pool. On the other hand, droplets at higher viscosity (100 and 1000 cSt) maintain their shape during cavity formation, showing pinning at the oil-water interface. The maximum diameter of the cavity was observed after it began to collapse. Upon normalizing the cavity energy, it was found that low viscosity silicone oil droplets transferred more than 90% of their impact energy to the cavity. However, less than 50% of the impact energy was transferred to the cavity for higher viscosity silicone oil droplets. While delineating some of the important dynamics of the phenomenon of droplet impact on liquid pool, this study has also effectively showcased the potential of machine learning in tracing interfaces, paving the way for its broader application in a multitude of multiphase flow scenarios that involve tracking of the interfacial motion and deformations.
## Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>Convolutional Neural Networks</td>
</tr>
<tr>
<td>$D_0$</td>
<td>Diameter of the droplet (m)</td>
</tr>
<tr>
<td>$E_c$</td>
<td>Total cavity energy ($\mu$J)</td>
</tr>
<tr>
<td>$E_{im}$</td>
<td>Droplet impact energy ($\mu$J)</td>
</tr>
<tr>
<td>$E_{kc(D)}$</td>
<td>Droplet kinetic energy ($\mu$J)</td>
</tr>
<tr>
<td>$E_{s(D)}$</td>
<td>Droplet surface energy ($\mu$J)</td>
</tr>
<tr>
<td>$E_{pe(c)}$</td>
<td>Cavity potential energy ($\mu$J)</td>
</tr>
<tr>
<td>$E_{s(c)}$</td>
<td>Cavity surface energy ($\mu$J)</td>
</tr>
<tr>
<td>$E_{w(c)}$</td>
<td>Wave swell energy ($\mu$J)</td>
</tr>
<tr>
<td>$g$</td>
<td>Acceleration due to gravity (m/s$^2$)</td>
</tr>
<tr>
<td>$h_p$</td>
<td>Pool depth (m)</td>
</tr>
<tr>
<td>$h^*$</td>
<td>Non-dimensional pool depth</td>
</tr>
<tr>
<td>$H$</td>
<td>Cavity depth (m)</td>
</tr>
<tr>
<td>$H_c$</td>
<td>Depth of cavity centroid from air-water interface (m)</td>
</tr>
<tr>
<td>ML</td>
<td>Machine learning</td>
</tr>
<tr>
<td>PMMA</td>
<td>Polymethyl methacrylate</td>
</tr>
<tr>
<td>$R_c$</td>
<td>Maximum cavity radius (m)</td>
</tr>
<tr>
<td>$Re$</td>
<td>Reynolds number</td>
</tr>
<tr>
<td>RPN</td>
<td>Region proposal network</td>
</tr>
<tr>
<td>$U$</td>
<td>Impingement velocity of droplet (m/s)</td>
</tr>
<tr>
<td>$V_c$</td>
<td>Volume of cavity ($m^3$)</td>
</tr>
<tr>
<td>$We$</td>
<td>Weber number</td>
</tr>
<tr>
<td>$\gamma_D$</td>
<td>Surface Tension of droplet (N/m)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Dynamic viscosity (N-s/m$^2$)</td>
</tr>
<tr>
<td>$\rho_D$</td>
<td>Density of droplet (kg/m$^3$)</td>
</tr>
<tr>
<td>$\rho_p$</td>
<td>Density of pool (kg/m$^3$)</td>
</tr>
<tr>
<td>$\nu$</td>
<td>Kinematic viscosity (cSt)</td>
</tr>
</tbody>
</table>

## Supplementary information

See supplementary material for Fig. 6 (Movie files depicting the impingement of droplets having viscosity of 1, 10, 100 and 1000 cSt on a water pool of non-dimensional height $h^* = 5$ at Weber number $We = 100$) and Fig. 7 (Movie files depicting the impingement and drop bounce back at Weber number $We = 50$ for droplets viscosity of 100 and 1000 cSt)
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Declarations

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Authors’ contributions

Mohammad Autif Shahdhaar: Data curation (lead); Formal analysis(lead); Investigation (equal); Methodology (equal); Writing – original draft (equal). Arpan Srivastava: Model training and implementation (lead), Data curation (equal), Writing – original draft (supporting). Atul Srivastava: Conceptualization (lead); Funding acquisition (lead); Investigation (equal); Methodology (equal); Project administration (lead); Supervision (lead); Writing – review and editing (lead).

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References


Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- S1We100h5.mp4
- S10We100andh5.mp4
- S100We50andh2.5.mp4
- S100We100andh5.mp4
- S1000We50andh1.mp4
- S1000We100andh5.mp4