

A study of condensation and frost dynamics on metallic and silicon substrates evaluated via a
computer vision model

by

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A.A., Johnson County Community College 2019

A.S., Johnson County Community College 2019

B.S., Kansas State University 2024

A THESIS

Submitted in partial fulfillment of the requirements for the degree

MASTER OF SCIENCE

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KANSAS STATE UNIVERSITY

Manhattan, Kansas

2026

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¹Abstract

Water droplets condensing and freezing on surfaces are ubiquitous phenomena that often must be managed rather than eliminated. Condensation and frosting on engineered surfaces play an important role in the performance and safety of many systems, including refrigeration, aerospace components, environmental controls, heat exchangers, and electronics applications. When water vapor condenses and subsequently freezes on a surface, the resulting droplet growth, coalescence, ice nucleation, and frosting mechanisms are strongly influenced by the physical and thermal characteristics of the substrate. Surface geometry, wettability, droplet mobility, and droplet pinning can all alter how condensed water accumulates and freezes. Understanding how these variables interact and affect condensation and frost behavior is key to the development of effective ice-phobic surfaces.

Two different types of surfaces, laser-patterned aluminum and silicon wafers coated with MoS₂, were the subject of investigation. Condensation and freezing experiments were performed on both surface types using the same experimental apparatus. For the metallic surfaces, experiments were conducted at ambient pressure, room temperature (i.e., 20 °C–23 °C), and at humidity levels of 39%–47% RH. The aluminum samples were cooled with a Peltier cooler set to -10°C. Two K-type OMEGA thermocouple probes (040G-6) were placed into precision, 1-mm-diameter holes machined in the edge of the sample to obtain a continuous, accurate surface temperature reading. The 1 mm holes were drilled to a depth of 10 mm. The average surface temperature was -8°C ± 0.5°C. Hole locations were spaced ±5 mm off the vertical centerline and centered on the horizontal centerline, 3.5 mm below the condensing surface.

Condensation from moist air was observed until the full field of view froze. The experiment was recorded using high-magnification video microscopy. Videos were then reduced to 1 frame per second for processing by a purpose-built YOLOv11 object detection model. The model extracted data on droplet population, average droplet diameter, droplet phase, and total surface coverage across the entire field of view. The YOLOv11-based architecture was trained on 1,300

^{1 1} Portions of this chapter were published in: Turner, Jane C., Aryan Singh Dalal, Hande Küçük McGinty, Melanie M. Derby, and Amy R. Betz. "Examining condensation and freezing behavior on a laser-patterned metallic surface using an AI neural network model." *Frontiers in Thermal Engineering* 6 (2026): 1808591.

manually annotated images and evaluated using standard object detection metrics. Following training, the model achieved a mean average precision at an intersection-over-union threshold of 0.50 of 78%, with a precision of 75% and a recall of 76.5%.

A bar of 6061 aircraft-grade aluminum with a mirror finish was used to create the substrate. 30 mm x 30 mm x 7mm sections were cut. A smooth portion of the unaltered bar stock was used as the control surface, and microtextured surfaces were created with a Pharos Laser and a 125 mm focal lens. The microtextured surface was generated using 15% of the total laser power. The laser created a pattern of parallel lines of a width of $100 \pm 5 \mu\text{m}$ spaced $150 \pm 5 \mu\text{m}$ apart. On the microtextured sample, the laser redeposited the material onto the surface, making a positive ridgeline. Tilting the stage of a scanning electron microscope at 70° to enable a clear side view of the microtextured sample. After imaging ten separate lines, sampled 5 mm apart, an average of 100 of the tallest peaks is found to be $6.8 \mu\text{m} \pm 0.98 \mu\text{m}$. The measured peak range is 3.3–9.5 μm .

Freezing behavior is strongly affected by metallic surface texture [9]. The smooth aluminum control surface reached full frost coverage in an average time of 419.5 s, while the microtextured aluminum surface froze completely in an average time of 139.5 s at a freezing rate $3\times$ times faster than the control. The faster freezing rate is attributed to the increased droplet pinning on the microtextured surface. Increased surface roughness leads to more pinning. This likely altered the dominant growth mechanisms, resulting in a smaller droplet size. It also provided more heterogeneous nucleation sites, improving heat transfer, and lowering the energy barrier to phase change. Freezing behavior is strongly affected by metallic surface texture. The smooth aluminum control surface reached full frost coverage in an average time of 419.5 s, while the microtextured aluminum surface froze completely in an average time of 139.5 s. A freezing rate $3x$ times faster than the control. The faster freezing rate is attributed to the increased droplet pinning on the microtextured surface. Increased surface roughness leads to more pinning. This likely altered the dominant growth mechanisms, resulting in a smaller droplet size. It also provided more heterogeneous nucleation sites, improving heat transfer and lowering the energy barrier to phase change.

The second part of this work examined how molybdenum disulfide application methods influenced condensation and frost formation on silicon (Si) substrates. Two different methods were used to coat the Si substrate with MoS₂. One was via chemical vapor deposition (CVD) with coating, and the other by mechanical exfoliation (ME). An uncoated silicon oxide (SiO_x) was used as a control surface. It is highly suspected that the Si wafers form an oxide later during the repeated cooling and thawing cycles. Contact angle measurements taken with a goniometer showed that the oxidized SiO_x control had a before contact angle of 83.02° and a contact angle of 91.33°. While MoS₂-ME and MoS₂-CVD had average contact angles of 92.74° and 104.37°, respectively. Visually, the CVD coating produced a more uniform distribution of small individual hexagonal MoS₂ flakes, while the ME surface contained comparably massive regions of irregularly distributed flake regions. These differences in surface structure produced distinct droplet growth and mobility behaviors.

The MoS₂ experiments were conducted under ambient conditions of approximately 19–21 °C and 45–51% RH. The Peltier cooler was set to –5 °C. Six trials were conducted for each surface. Microscope videos were reduced to 1 frame per second and processed using the vision model for analysis. Although early nucleation and late-stage phase identification remained challenging, the model reliably captured droplet population and diameter once droplets reached approximately 10 µm in diameter. The model reports a single confidence value for all parameters examined at each instance. The model reached approximately 75% confidence at average times of 37 s for the control, 47 s for MoS₂-CVD, and 24 s for MoS₂-ME.

The average maximum droplet populations were 1510 for the control, 1753 for MoS₂-CVD, and 1170 for MoS₂-ME. The average droplet diameters at initial freezing were 25.68 µm for the control, 39.92 µm for MoS₂-CVD, and 33.6 µm for MoS₂-ME. The average surface coverage values were 55.98% for the control, 64.40% for MoS₂-CVD, and 50.30% for MoS₂-ME. The control surface had the longest average freezing time at 621 s, followed by MoS₂-CVD at 425 s and MoS₂-ME at 242 s. Thus, MoS₂-ME froze ~ 2.5× faster than the control and ~ 1.7× faster than MoS₂-CVD. The power law values are calculated averages across each test series. The population exponents are as follows: $p_{ME} \propto t^{-1.3}$, $p_{CVD} \propto t^{-1.3}$, and $p_{Control} \propto t^{-0.91}$. However, this pattern is not

inverted in the diameter's exponent order as would be expected and is: $d_{CVD} \propto t^{0.73}$, $d_{Control} \propto t^{0.69}$, and $d_{ME} \propto t^{0.63}$.

The MoS₂-CVD surface produced the maximum average values for droplet population, average droplet diameter at initial freezing, and surface coverage before freezing. These results suggest that the more uniform CVD coating induced a Cassie state, thereby promoting droplet mobility and increasing coalescence events. The irregular distribution of mechanically exfoliated MoS₂ flakes likely induced a Wenzel state, thereby increasing droplet pinning, the solid–liquid contact area, and the number of heterogeneous nucleation sites. The above results may suggest that the faster freezing rate of the ME was influenced by greater pinning and increased nucleation sites.

Across both substrate sets, the results show that engineered surfaces can strongly alter condensation and freezing dynamics. On metallic aluminum, laser texturing increased droplet pinning and accelerated freezing relative to the control. On silicon substrates, different MoS₂ application methods influenced droplet mobility and freezing time. Together, these studies further the collective understanding of the effects that surface topography, coatings, and surface wetting properties play in governing condensation growth regimes and frost dynamics.

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Acknowledgements

I would first and foremost like to acknowledge my advisors, Dr. Amy Rachel Betz and Dr. Melanie Derby, for giving me the opportunity to pursue an advanced degree. Education is a privilege, and I am deeply grateful for their time, patience, creativity, thoughtful discussions, and wisdom they have shared with me throughout this process. Their guidance has shaped not only this work, but who I am as a researcher. I have no doubt that this degree will carry me far and open doors to many exciting opportunities that would not have been possible otherwise.

To Dr. McGinty and her team in Computer Science, who built the ML model, my deepest appreciation for your hard work in the development of this incredible tool. I would like to thank IER for allowing me the use of their environmental chamber. I would also like to thank the members of the CHILLAB for their support and help. This research was graciously supported by the U.S. National Science Foundation through Grant No. 2423634. A special thank-you goes to our colleagues Rafid Hussenin, Issac Omembe, Asif Raihan, Arijit Roy, and Kevin Myren for their invaluable help with sample creation. Your contributions were essential.

I would also like to thank my mother and family members for their continued love and support. To my very kind and patient partner: thank you for the meals, snacks, walks, and steady reassurance. The small things are often the most vital to success. Last but not least, thank you to my dear friends, who always offered an open ear, a ready wit, and just the right amount of academic commiseration: Thank You and Cheers.

Dedication

For my Paternal and Maternal Grandfathers, Ted C. Turner and Dr. David S. Silvert, MD.
For my dear friends: Ben J. Karbaumer, James Cavanguah, and Daniel Yost, who have since
walked on. You are dearly missed.

Chapter 1 : Introduction and Literature Review

²Water droplets condensing and freezing on surfaces is a ubiquitous phenomenon that often must be managed rather than eliminated. From air conditioners freezing over in the summer to icy sidewalks in the winter, the consequences of uncontrolled freezing range from minor inconveniences to serious hazards. Delayed flights, highway pileups, and city-wide power outages during winter storms are just a few examples of how ice formation can disrupt significant infrastructure and endanger lives. On average, severe winter weather costs the U.S. economy approximately \$2.5 billion annually [5]. These events strain resources, disrupt transportation and energy systems, and pose risks to human health and safety [6]. Therefore, understanding the mechanisms of freezing is not only a scientific challenge but also a practical necessity for designing safer and more resilient systems.

Recent research has deepened our understanding of condensation frosting, a multi-stage process involving droplet nucleation from the condensation of moist air, coalescence, initial icing, frost halo formation, ice bridging, and frost densification [7], [8]. This has led to the development of engineered surfaces to control the propagation of freezing, such as superhydrophobic and microstructured materials, which delay or suppress ice formation without requiring external energy input. These surfaces reduce droplet residence time and inhibit ice nucleation, and offer sustainable solutions for thermal management and environmental control [7], [8].

Consider receiving a glass of iced lemonade on a hot afternoon. First, the outside of the glass is dry, free of any moisture; then it quickly becomes fogged as the moist summer air condenses on the surface of the glass. As time passes, the droplets grow from a fine mist into a slick surface dotted with droplets. If the glass sits long enough, it will begin to sweat and shed droplets and replace the old droplets with new ones [9]. This is a common place example of condensation - the phase change in which a vapor becomes a liquid [10].

^{2 2} Portions of this chapter were published in: Turner, Jane C., Aryan Singh Dalal, Hande Küçük McGinty, Melanie M. Derby, and Amy R. Betz. "Examining condensation and freezing behavior on a laser-patterned metallic surface using an AI neural network model." *Frontiers in Thermal Engineering* 6 (2026): 1808591.

Mechanical versions of this process are used in many kinds of applications. Condensers act as a specialized heat exchanger that converts a vapor into a liquid by lowering the temperature of the vapor to or below its saturation point. Real-world applications include power generation, HV/AC, refrigeration, chemical production, and other manufacturing processes. [11].

The dew point and relative humidity (RH) are two major interconnected factors of condensation of moist air. The dew point is the temperature at which air becomes saturated with water vapor. When warm, moist air cools, its capacity to hold water vapor decreases. If the temperature drops to the dew point or lower, the excess vapor condenses into tiny liquid droplets [12]. The availability of water as vapor in a given volume of air is known as relative humidity (RH) [12]. The amount of water vapor in the air is dependent on temperature. For example, for a 95°F day in the summer with 80% RH, there will be a ~32g of water in a cubic meter of air [13]. However, for a damp, misty fall day of 65°F and 80% RH, there will be only ~12.5g of water for every m³ of air [13], resulting in a 19.5g/m³ difference in available water.

The lemonade glass example illustrates the progression of the two main forms of condensation: dropwise condensation (DWC) and filmwise condensation (FWC) (Figure 1.1). For dropwise condensation from moist air, nucleation on a surface begins when gaseous water molecules form nanoscale droplets on the cooler surface. This is known as direct vapor deposition. These droplets then coalesce into larger droplets. If the surface exhibits hydrophobic tendencies, the droplets continue to grow as distinct entities, with a dry void between droplets. Growth in DWC is driven via coalescence and continued by direct vapor deposition. Should the surface be hydrophilic, the condensate wets the surface and forms a continuous liquid film. The liquid layer sits between the vapor and the cold surface. This leads to thermal resistance, as the mode of heat transfer shifts to conduction through the condensate film [14].

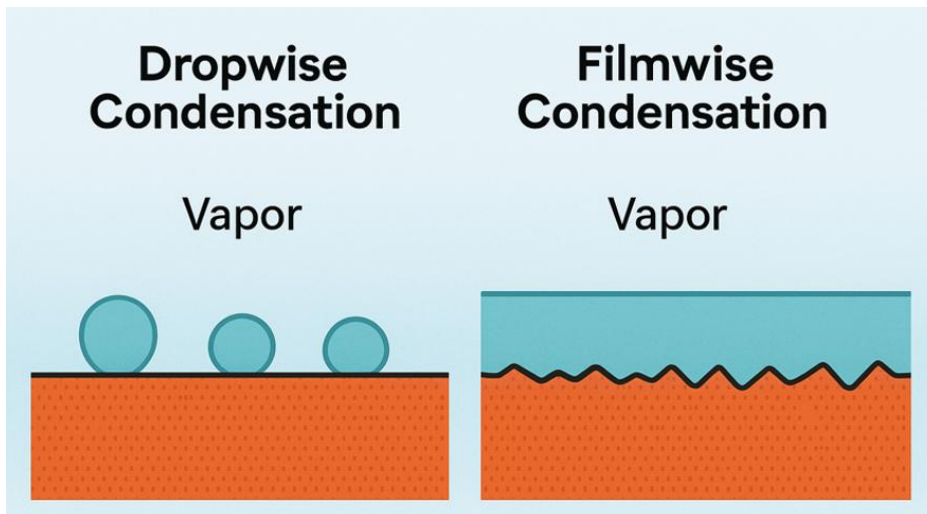


Figure 1.1:
 (Left) dropwise condensation (DWC),
 (Right) filmwise condensation. Image created with Copilot.
 Prompt “Please create an image explaining dropwise and filmwise condensation.”, Copilot – GPT 5.5 Think deeper, Microsoft, 10/10/2025

Condensation and droplet dynamics from nucleation, propagation, coalescence rates, and subsequent freezing are all affected by the substrate’s texture [7]. Surface wetting characteristics describe how liquid droplets interact with a solid surface. The green dot in Figure 1.2A describes the triple point, where the liquid, solid, and air meet. The angle created between the surface and the droplet is known as the contact angle α (Figure 1.2A-C). A hydrophilic surface creates a contact angle (α) of less than 90° (Figure 1.2B). A hydrophobic surface has a contact angle of 90° or greater (Figure 1.2C). Contact angles over 150° are considered superhydrophobic. The contact angle controls the droplet shape, the contact area with a surface, and the rate of heat transfer between the water and the substrate [15] [16]. In addition to the importance of dictating droplet formation in condensation, the contact angle is significant in ice formation [16].

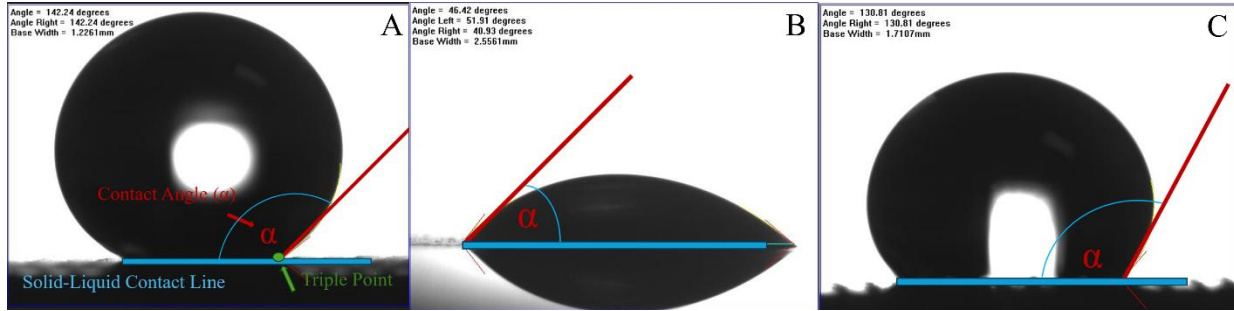


Figure 1.2: A) diagram of a water droplet on an Al microtextured surface, delineating the triple point (green), solid-liquid contact line (blue), and how the contact angle α is measured (red). B) Water droplet on a hydrophilic, water-loving surface. C) Water droplet on a hydrophobic, water-fearing surface.

The micro and nanostructures of a surface strongly influence how water wets a surface by altering the liquid-solid contact area between the droplet and the solid. Additionally, surface roughness influences the location of preferential nucleation sites. On smooth surfaces, freezing starts through heterogeneous nucleation of ice, often at edges, defects, or rough spots, due to their ability to lower the activation energy for ice formation compared to homogeneous nucleation in the bulk liquid [17].

On a chemically smooth surface, wetting is primarily controlled by the material's surface energy. However, on a rough surface, the droplet may penetrate partially or fully into voids (Figure 1.3). These two behaviors are described by Cassie–Baxter and Wenzel states. In a Wenzel state, water fills the voids in the roughened surface, making complete contact with the surface (Figure 1.3 Left) [18]. In the Cassie–Baxter state, air remains trapped beneath the droplet, reducing the solid–liquid contact area (Figure 1.3 Right) [19].

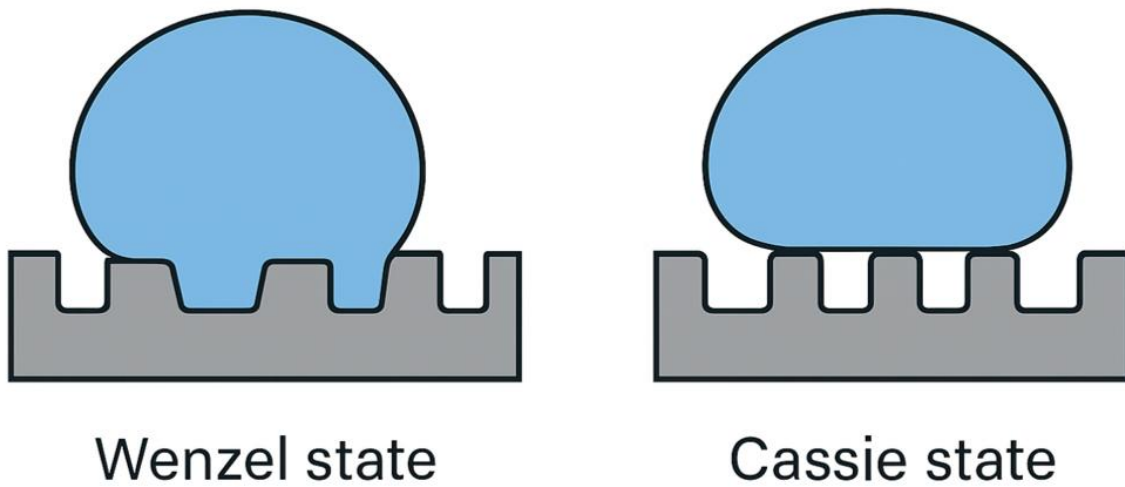


Figure 1.3: Left droplet in Wenzel State, Right droplet in Cassie State. Image created with hand sketch and Copilot. Prompt “Please create an image of the two different states from sketch.”, Copilot – GPT 5.5 Think deeper, Microsoft, 4/28/2026

In the Wenzel state, roughness amplifies the material's natural wetting behavior. If the surface is already hydrophilic, added roughness usually makes it appear even more so as the water spreads into the voids [15]. If the surface is hydrophobic, roughness can make it appear to have an increased apparent contact angle [18]. In the Cassie–Baxter state, roughness can make a surface highly water-repellent, due to the droplet resting on top of micro or nano scale structures with air trapped underneath (Figure 1.3 Right) [19]. This reduced contact between the water and the solid often leads to high contact angles and greater droplet mobility [19].

The ability of a surface to pin a droplet in place often plays a significant role in the dropwise condensation behavior exhibited. Contact angle hysteresis is the difference between the advancing and receding contact angles [20]. Hysteresis can also explain why a liquid droplet adheres strongly to a surface rather than rolling off [21]. When a surface exhibits high hysteresis, the three-phase contact line becomes anchored to surface defects, requiring a significant force to advance or recede, thereby immobilizing droplets [22], [23]. Micro and nano

scale roughness can further enhance pinning when droplets adopt a Wenzel state thereby increasing the effective solid–liquid contact area and increasing resistance to motion [18], [24]. In condensation, pinning suppresses droplet migration and coalescence-induced shedding, prolonging droplet residence time on the surface, and allowing droplets to reach thermal equilibrium with the substrate [25], [26].

Droplet growth also depends strongly on wetting behavior. Beysens and Knobler (1986) determined that dropwise condensation on non-wetting surfaces was characterized by a power law scaling of droplet growth, unlike filmwise condensation. For these scaling laws, droplet diameter was proportional to t^x as determined by investigating the growth rate of single droplets. Coalescence of droplets accelerated the growth rate of a single droplet and affected the total droplet population by re-nucleating droplets in the void created by coalescing droplets [27]. Importantly, the droplet population was shown to grow by power law scaling with respect to time [25]. Subsequent studies linked observed power law exponents to distinct physical growth mechanisms and environmental conditions [28], [29]. Leach et al. (2006) showed that droplet growth was size-dependent: small droplets grew primarily through surface diffusive transport, while larger droplets grew mainly through direct vapor condensation. Furthering this understanding to realistic atmospheric conditions, Castillo et al. demonstrated that ambient relative humidity primarily affects the power law exponent in regimes dominated by direct condensation [29]. However, once coalescence becomes dominant, droplet growth defaults to a humidity-independent scaling behavior. Dropwise condensation is a coalescence-driven scaling process and is often modeled using power laws [25], [28], [29].

At temperatures below freezing and the dew point, condensed droplets will freeze. Droplets formed by heterogeneous nucleation follow a particular set of rules when forming ice [2]. The ice phase is ignited by nucleating an ice embryo. In order to form the ice embryo, or seed crystal, the liquid water droplets must be cooled to 0°C or lower and remain in a liquid state, known as supercooling [2]. Heterogeneous nucleation is much more efficient because water molecules optimize growth on existing surfaces, such as dust or surface geometry, to form the ice embryo. The existing structure significantly lowers the Gibbs free-energy barrier compared with homogeneous nucleation.

Formation of the embryo occurs in two ways: either via vapor deposition of an ice seed crystal into an existing droplet, or nucleation of an ice embryo within the supercooled water. Once an ice embryo is formed on the substrate, it is reclassified as an ice nucleus. The ice nucleus's success in growing past criticality is influenced by the mass of the droplet, the shape of the crystal, the height and radius of the crystal shape, the proportionality of the faces of the crystal, the number of ice embryos composing the ice nuclei, and the partial pressure of the vapor surrounding the droplet [2]. Relative humidity, contact angle of the droplet, and the size and species of the nucleating particle, also influence the success of ice growth within the droplet [30].

The methods by which a freezing front propagates through a droplet field include cascade, stochastic, or ice-bridging behaviors [4]. The surface geometry and droplet distribution on the substrate dictate the most likely freezing mechanism [31]. When cascade freezing starts in a droplet field, it is initiated by a single supercooled droplet forming an ice nucleus and freezing almost instantaneously. This causes a reascent reaction in the initial drop [32], which goes from liquid to solid, to slush in the time span of milliseconds [32]. This rapid phase change releases latent heat and, consequently, the original droplet releases a vapor gradient of airborne tiny ice seed crystals. As these seed crystals reach their neighboring supercooled droplets, their presence can cause local supersaturation and the spontaneous formation of microscopic ice crystals [32]. This can trigger nucleation by contact freezing of the neighboring droplet, resulting in a freezing cascade [32]. The nature of cascade bridging is hyperlocal and is dependent on having inter-droplet interactions. This is typically due to small distances between the droplets, but it can also be influenced by factors such as substrate thermal conductivity [14]. Micropatterned hydrophilic spots on a surface promote uniform droplet spacing and induce cascade behavior [31].

Stochastic freezing stems from large distances between droplets and frequently occurs when dendrites fail to form successful bridges with close neighbors [33], leading droplets to freeze independently without bridging. Isolated from its neighbors, a droplet may successfully form a stable ice nucleus and freeze. This random event can trigger a cascading event or seemingly separate (missing word?), and freezing events [32]. Cascade and stochastic freezing

are most often observed on grooved or sintered substrates, as the more complex topography of a surface is less amenable to ice bridging [4]. The probability of a stochastic mechanism being predominant is increased with the following factors: temperature decreases, large droplet volume grows, an increase in the liquid-solid contact area, or defects in the surface are present, including dust or impurities [34].

It has been observed that in plain, smooth surfaces, the predominant freezing mechanism is ice bridging. Creating space between droplets can slow their overall growth [33]. Nath et al. (2020) investigated condensation frosting on chilled surfaces, focusing on inter-droplet ice bridging, in which ice dendrites propagated from the frozen droplets to adjacent supercooled liquid droplets. Ice bridges formed because frozen droplets acted as humidity sinks. For ice bridging, nearby liquid droplets evaporated and deposited vapor. The success of the bridge was entirely dependent on the geometry of droplets, droplet size, and spacing, and was not dependent on humidity, surface, or surface wettability [33]. For a given pair of droplets, the maximum extent to which an ice bridge could grow was geometrically constrained by the distance from the edge of the frozen droplet to the center of the liquid droplet. In dropwise condensation formation, the amount of water vapor available is a key factor in predicting the size and growth rate of droplets and their subsequent freezing on surfaces [35].

Zhao et al. (2021) investigated the effects of ice suppression via passive surface engineering by the introduction of microgroove surfaces with added nucleation sites via “nanoblades” [36]. Copper samples were milled to create semicircular peaks and valleys. The secondary step created cactus-like spines on the surface. This secondary surface yielded directionally dependent wetting behavior. The combination of microgrooves and nanoblades effectively controlled the size and distribution of condensed droplets, thereby aiding overall frost reduction. The introduction of hierarchical surfaces to a substrate enabled planned nucleation sites, thereby pinning the droplet in place and controlling access to available water vapor.

Images visualizing condensed and frozen droplets contain a substantial number (i.e., hundreds to thousands) of droplets; thus, this problem is well-suited to an artificial neural

network using a machine learning (ML) technique. Machine learning techniques are becoming globally accessible, and the application of different ML techniques is leading to more efficient data analysis for object identification of key variables within videos and imaging. Najafian and Mortazavi (2025) conducted a study to predict droplet evaporation and falling rates using machine learning models. After performing 544 numerical simulations with the front-tracking method, they compared the results of five machine learning (ML) algorithms trained on the same data set. The artificial neural network model achieved the highest accuracy, with an R^2 value of approximately 0.999 for both evaporation and fall rate predictions. Showing better performance than the other models [37]. Yee et al. (2024) analyzed the morphological evolution of splashing versus non-splashing drops using explainable artificial intelligence. A feedforward neural network was trained to classify image sequences as splashing or non-splashing, achieving over 96% accuracy [37], [38]. The high accuracy rates of Neural Networks helped our team choose this type of ML for our model.

The research objectives of this paper are to observe and understand the behaviors of water vapor condensing into liquid droplets and their subsequent freezing on a variety of substrates and altered microsurfaces using a neural network model. Since droplet pinning and coalescence impact freezing behavior [4], The neural network model is developed to determine droplet counts and average sizes. The ability to comprehensively count both the droplet population and droplet diameter at a given time aids our understanding of droplet formation via coalescence or direct vapor deposition, and of their subsequent freezing patterns.

Chapter 2 : Examining condensation and freezing behavior on a laser-pattered metallic surface using an AI neural network model ³

2.1 Abstract

Introduction: Condensation and freezing of water droplets on solid surfaces occur in a wide range of natural and engineered systems; uncontrolled or unwanted ice formation poses significant challenges to performance and safety. Surface texture greatly influences droplet nucleation, growth, coalescence, and freezing mechanisms by affecting wettability and droplet pinning.

Method: In this paper, the effects of a microtextured aluminum surface are visualized at high magnification (e.g., 600×) during condensation from moist air at 20-23°C and 39-47% RH. Condensed droplet images are processed with an artificial intelligence (AI) model.

Results and Discussion: Different textures measurably affect droplet condensation dynamics and subsequent freezing behavior. A neural network-based object detection model was developed to quantify droplet population, average diameter, phase state, and surface coverage across entire fields of view. The model was trained on over 1,300 images. The detection model provided statistically robust insights into the relationships of condensation dynamics, surface texture, and freezing behavior. The AI-derived measurements for condensed droplets show that both droplet population decline and diameter growth follow power law scaling over time. The microtextured surface displayed smaller power law exponents compared to the smooth control surface. This indicates a shift in condensation behavior caused by increased droplet pinning and decreased mobility on the microtextured surface. These changes are also linked to much faster freezing. The microtextured surfaces achieved full frost coverage at an average time of 139.5 seconds, which is roughly three times quicker than smooth substrates with an average freezing

³ Portions of this chapter were published in: Turner, Jane C., Aryan Singh Dalal, Hande Küçük McGinty, Melanie M. Derby, and Amy R. Betz. "Examining condensation and freezing behavior on a laser-patterned metallic surface using an AI neural network model." *Frontiers in Thermal Engineering* 6 (2026): 1808591.

time of 419.5 seconds. The findings reveal that surface-induced pinning directly influenced condensation growth and subsequent freezing behavior.

2.2 Introduction

Water droplets condensing and freezing on surfaces is a ubiquitous phenomenon that often must be managed rather than eliminated. From air conditioners freezing over in the summer to icy sidewalks in the winter, the consequences of uncontrolled freezing range from minor inconveniences to serious hazards. Delayed flights, highway pileups, and city-wide power outages during winter storms are just a few examples of how ice formation can disrupt significant infrastructure and endanger lives. On average, severe winter weather costs the U.S. economy approximately \$2.5 billion annually [5]. These events strain resources, disrupt transportation and energy systems, and pose risks to human health and safety [6]. Therefore, understanding the mechanisms of freezing is not only a scientific challenge but also a practical necessity for designing safer, more resilient systems.

Recent research has deepened our understanding of condensation frosting, a multi-stage process involving droplet nucleation from the condensation of moist air, coalescence, initial icing, frost halo formation, ice bridging, and frost densification [7], [8]. This has led to the development of engineered surfaces to control the propagation of freezing, such as superhydrophobic and microstructured materials, which delay or suppress ice formation without requiring external energy input. These surfaces reduce droplet residence time and inhibit ice nucleation and offer sustainable solutions for thermal management and environmental control [7], [31].

For condensation from moist air and subsequent freezing, nucleation, propagation, coalescence rates, and droplet dynamics are all affected by the substrate's texture [7]. On smooth surfaces, freezing starts through heterogeneous nucleation of ice, often at edges, defects, or rough spots, due to their ability to lower the activation energy for ice formation compared to homogeneous nucleation in the bulk liquid [4]. Zhao et al. (2021) investigated the effects of ice suppression via passive surface engineering by the introduction of microgroove surfaces with added nucleation sites via “nanoblades” [36]. Copper samples were milled to create semicircular peaks and valleys. The secondary step created cactus-like spines on the surface. This secondary surface yielded

directionally dependent wetting behavior. The combination of microgrooves and nanoblades effectively controlled the size and distribution of condensed droplets, thereby aiding overall frost reduction. The introduction of hierarchical surfaces to a substrate enabled planned nucleation sites, thereby pinning the droplet in place and controlling access to available water vapor.

Beysens and Knobler (1986) determined that dropwise condensation on non-wetting surfaces was characterized by a power law scaling of droplet growth, unlike filmwise condensation. For these scaling laws, droplet diameter was proportional to t^x as determined by investigating the growth rate of single droplets. Coalescence of droplets accelerated the growth rate of a single droplet and affected the total droplet population by re-nucleating droplets in the void created by coalescing droplets [27]. Importantly, the droplet population was shown to grow by power law scaling with respect to time [25]. Subsequent studies linked observed power law exponents to distinct physical growth mechanisms and environmental conditions [28], [29]. Leach et al. (2006) showed that droplet growth was size-dependent: small droplets grew primarily through surface diffusive transport, while larger droplets grew mainly through direct vapor condensation. Furthering this understanding to realistic atmospheric conditions, Castillo et al. [29] demonstrated that ambient relative humidity primarily affects the power law exponent in regimes dominated by direct condensation. However, once coalescence becomes dominant, droplet growth defaults to a humidity-independent scaling behavior. Dropwise condensation is a coalescence-driven scaling process and is often modeled using power laws [25], [28], [29].

The ability of a surface to pin a droplet in place often plays a significant role in the dropwise condensation behavior exhibited. When a surface exhibits high hysteresis, the three-phase contact line becomes anchored to surface defects, requiring a significant force to advance or recede, thereby immobilizing droplets [22], [23]. Micro and nano-scale roughness can further enhance pinning when droplets adopt a Wenzel state, thereby increasing the effective solid–liquid contact area and increasing resistance to motion [18], [24]. In condensation, pinning suppresses droplet migration and coalescence-induced shedding, prolonging droplet residence time on the surface, and allowing droplets to reach thermal equilibrium with the substrate [25], [26].

At temperatures below the freezing and dew point, condensed droplets will freeze. The methods by which a freezing front propagates through a droplet field include cascade, stochastic, or ice-bridging behaviors [4]. The surface geometry and droplet distribution on the substrate dictate the most likely freezing mechanism [31]. Cascade bridging is dependent on having inter-droplet interactions, typically due to small distances between the droplets but can also be influenced by factors such as substrate thermal conductivity [14]. Micropatterned hydrophilic spots on a surface promote uniform droplet spacing and cascade behavior [31]. Stochastic freezing stems from large distances between droplets, as dendrites fail to form successful bridges with close neighbors. This leads droplets to freeze independently, without bridging. Cascade and stochastic freezing are most often observed on grooved or sintered substrates [4].

Nath et al. (2020) investigated condensation frosting on chilled surfaces, focusing on inter-droplet ice bridging, in which ice dendrites propagated from the frozen droplets to adjacent supercooled liquid droplets. Ice bridges formed because frozen droplets acted as humidity sinks. For ice bridging, nearby liquid droplets evaporated and deposited vapor. The success of the bridge was entirely dependent on the geometry of droplets, droplet size, and spacing, and was not dependent on humidity, surface, or surface wettability [33]. For a given pair of droplets, the maximum extent to which an ice bridge could grow was geometrically constrained by the distance from the edge of the frozen droplet to the center of the liquid droplet. In dropwise condensation formation, the amount of water vapor available is a key factor in predicting the size and growth rate of droplets and their subsequent freezing on surfaces [35]. It has been observed that in plain, smooth surfaces, the predominant freezing mechanism is ice bridging. Creating space between droplets can slow their overall growth [33].

Images visualizing frozen and condensed droplets contain a substantial number (i.e., hundreds to thousands) of droplets; thus, this problem is well-suited to an artificial neural network using a machine learning (ML) technique. Machine learning techniques are becoming globally accessible, and the application of different ML techniques is leading to more efficient data analysis for object identification of key variables within videos and imaging. Najafian and Mortazavi (2025) conducted a study to predict droplet evaporation and falling rates using machine learning models. After performing 544 numerical simulations with the front-tracking method, they compared the

results of five machine learning (ML) algorithms trained on the same data set. The artificial neural network model achieved the highest accuracy, with an R^2 value of approximately 0.999 for both evaporation and fall rate predictions. Showing better performance than the other models. Yee et al. (2024) analyzed the morphological evolution of splashing versus non-splashing drops using explainable artificial intelligence. A feedforward neural network was trained to classify image sequences as splashing or non-splashing, achieving over 96% accuracy [37], [38]. The high accuracy rates of Neural Networks helped our team choose this type of ML for our model.

The research objectives of this paper are to understand the impacts of surface texture on the freezing mechanisms of aluminum surfaces using a neural network model. Since droplet pinning and coalescence impact freezing behavior [4], the neural network model is developed to determine droplet counts and average sizes. The ability to comprehensively count both the droplet population and droplet diameter at a given time aids our understanding of droplet formation via coalescence or direct vapor deposition, and of their subsequent freezing patterns.

2.3 Methods

The experimental apparatus to observe condensation from moist air and subsequent freezing is shown in Figure 2.1 [4], [27], [39]. A Leica DVM2500 microscope is used for all experiments. The sample is placed on a TE Technology Peltier cooler (TE-127-1.0-2.5) and attached using Omega High Temp & Conductive Paste thermal paste (OT-201-16, thermal conductivity of 2.3 W/mK). The Peltier cooler is attached to a custom aluminum water-cooled heat sink, with

additional thermal paste, which rests on the microscope stage in a ceramic box. A NESLAB RTE-11 water chiller is set to 10 °C and runs for at least 30 min prior to the experiment.

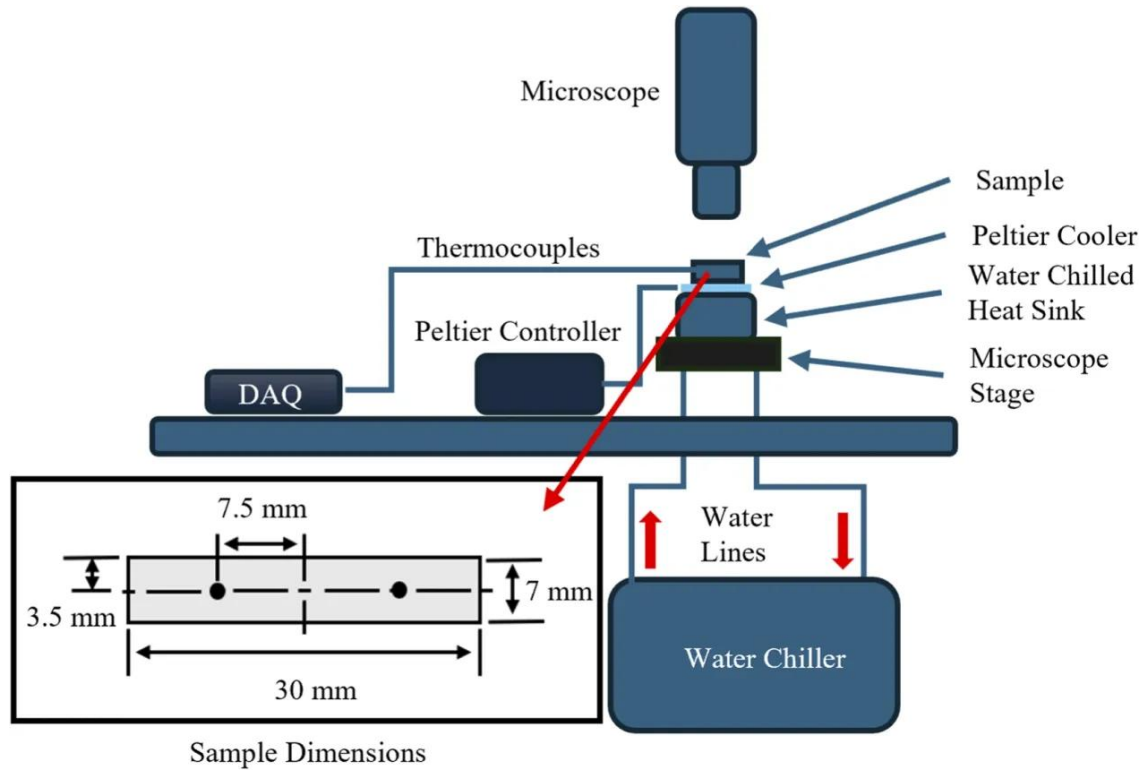


Figure 2.1 Schematic of the experimental apparatus to visualize condensation and subsequent freezing, which is placed in an environmental chamber. The lower-left inset provides a detailed schematic of the test surface's side view.

Two K-type OMEGA thermocouple probes (040G-6) are placed into precision 1-mm-diameter holes machined in the edge of the sample to obtain a continuous, accurate surface temperature reading. Calibration of thermocouples at three different temperatures demonstrated an accuracy of ± 0.5 °C. The 1 mm holes were drilled to a depth of 10 mm. Hole locations were spaced ± 5 mm off the vertical centerline and centered on the horizontal centerline, 3.5 mm below the condensing surface, also shown in Figure 2.1. An Omega data acquisition system (OM-USB-TC-AI) is used to record the surface temperature at the rate of 1 Hz. The Peltier cooler is driven by a separate TE Technology control unit (TC-720) and is managed by the manufacturer's software on the desktop computer. The microscope operation is managed via Leica's application suite.

2.3.1 Sample Creation and Characterization:

A bar of 6061 aircraft-grade aluminum with a mirror finish was used as the substrate. A smooth surface was used as a control, and microtextured surfaces were created with a Pharos Laser and a 125 mm focal lens. The laser parameters were as follows: fluence of 0.62 J/cm^2 , wavelength 800–1,056 nm, pulse duration 184 fs, repetition rate 50 kHz (kiloHertz), scanning speed 10 mm/sec. The microtextured surface was generated using 15% of the total laser power. The laser created a pattern of parallel lines of a width of $100 \pm 5 \text{ }\mu\text{m}$ spaced $150 \pm 5 \text{ }\mu\text{m}$ apart (Figure 2.2). A Hitachi S 3000 N VP-SEM was used for inspection. The SEM accelerating voltage was 15,000 V, working distance 45,900 μm , and a backscattered electron detector type was used.

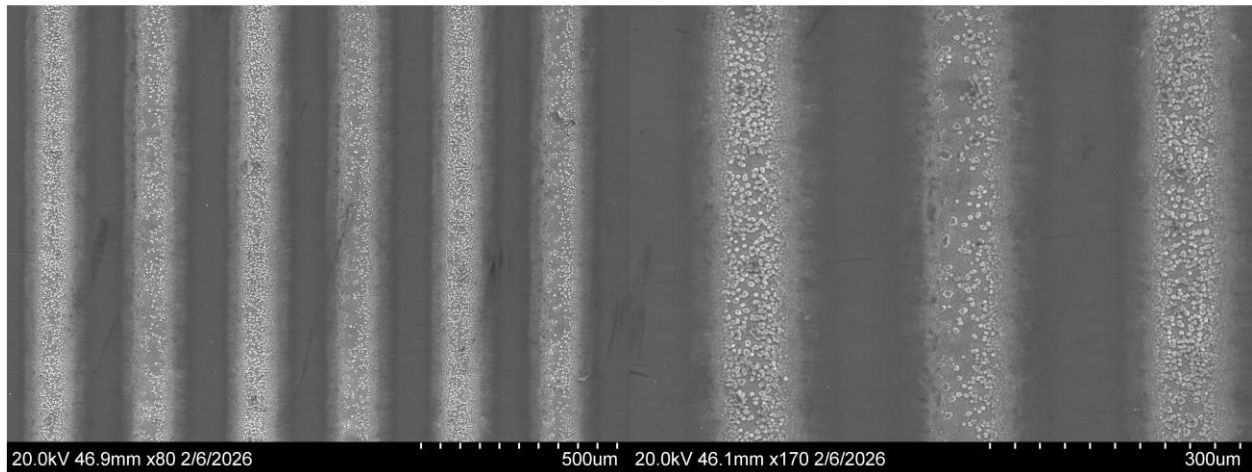


Figure 2.2 SEM images of the microtextured surface show the general pattern configuration of laser lines with a width of $100 \text{ }\mu\text{m}$ spaced $150 \text{ }\mu\text{m}$ apart. SEM accelerating voltage 15,000 V, working distance 45,900 μm . A backscattered electron detector type was used.

On the microtextured sample, the laser redeposited the material onto the surface, making a positive ridgeline (Figure 2.3). These topographical features will be referred to as peaks and plains (Figure 2.3). The peaks are not of a uniform height. The stage of a scanning electron microscope was tilted at 70° to enable a clear side view of the microtextured sample. After imaging ten separate lines, sampled 5 mm apart, an average of 100 of the tallest peaks was found to be $6.8 \text{ }\mu\text{m} \pm 0.98 \text{ }\mu\text{m}$. The measured peak range was 3.3–9.5 μm .

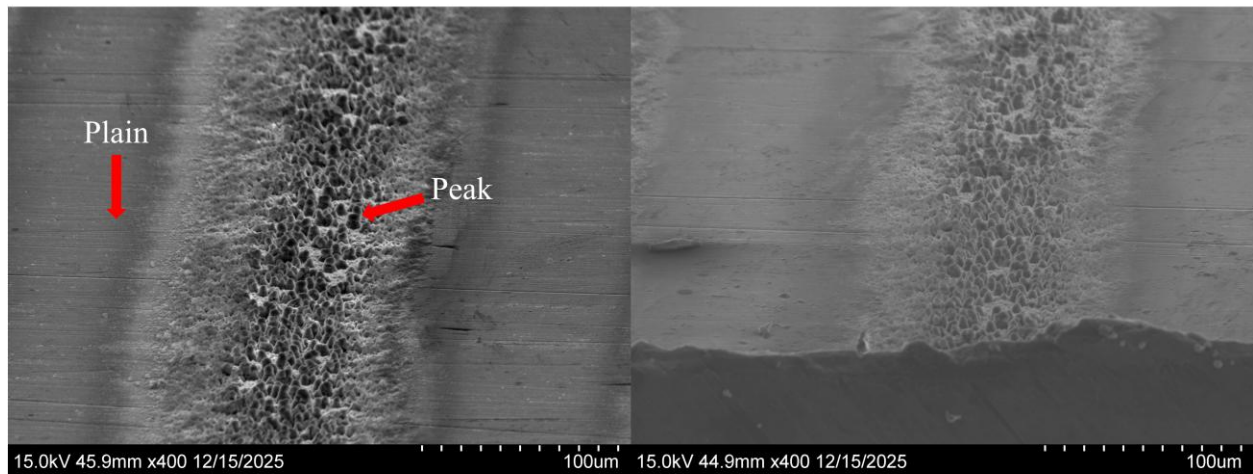


Figure 2.3 SEM images of the microtextured samples resulting from laser manufacturing. The image on the left was taken at x400 and +70° from horizontal. The image on the right is the same region as the sample but taken at the edge of the sample.

The wetting characteristics were determined using a goniometer. It was found that the control surface is hydrophobic with an average contact angle $94^\circ \pm 3.71^\circ$. The microtextured surface displayed an interesting directional wetting behavior. Although hydrophobic, when the line pattern was aligned with the goniometer lens, the contact angle was $129^\circ \pm 3.08^\circ$. However, when lines were perpendicular to the goniometer lens, the contact angle was $96.7^\circ \pm 5.29^\circ$.

2.3.2 Operational Procedures:

Testing was held in an environmental chamber within the Institute for Environmental Research at Kansas State University. The experiment was conducted in the fall; air temperatures were 20 °C–23 °C and relative humidities were 39%–47% RH, ambient air conditions were maintained. The sample was prepared for observation by first inserting two thermocouples into the holes with thermal paste. Surface temperatures were measured at a rate of 1 Hz during the experiments. The sample was adhered with additional thermal paste applied to the top of the Peltier cooler to minimize trapped air and maximize thermal contact.

The Peltier controller was set to -10°C . Once the Peltier cooler was turned on, the surface temperature (as measured by the embedded thermocouples) reached $-8^\circ\text{C} \pm 1^\circ\text{C}$ within 20–30 s. Condensation from the moist air and subsequent freezing was observed. The experiment

was considered complete when the entire field of view was fully frozen. A video of each experiment was recorded at 600 $\times$ magnification, yielding a field of view of 0.51 x 0.38 mm; high magnification was required to observe initial nucleation. Each microscope image had 1.92×10^6 total pixels with an area of 318×316 nm/pixel. Air temperature, surface temperature, relative humidity, and the total time until freezing were recorded.

After initial data collection, the video was reduced to a rate of 1 frame per second (1 fps). This frame rate was chosen to create a manageable file size of the dataset for processing via the purpose-built AI model. The model measured the number of droplets, the average droplet diameter, the droplet phase (i.e., liquid water or ice), and the water or ice area as a percentage of the total area.

2.3.3 Model Architecture and Training

The droplet detection model was implemented using a YOLOv11 architecture. Training images were resized to a fixed input resolution of 640×640 pixels prior to model training. The dataset consisted of manually annotated droplets used to generate bounding boxes for the water class. Figure 2.4 shows pre- and post-annotations on droplet fields or liquid water, a mix of liquid water and ice, and ice images. Standard preprocessing steps included image normalization and resizing, while data augmentation techniques, such as random horizontal and vertical flips, scaling, rotation, and brightness/contrast adjustments were applied to improve model robustness. The model was trained using a batch size of 16 with the Adam optimizer and an initial learning rate of 0.001.

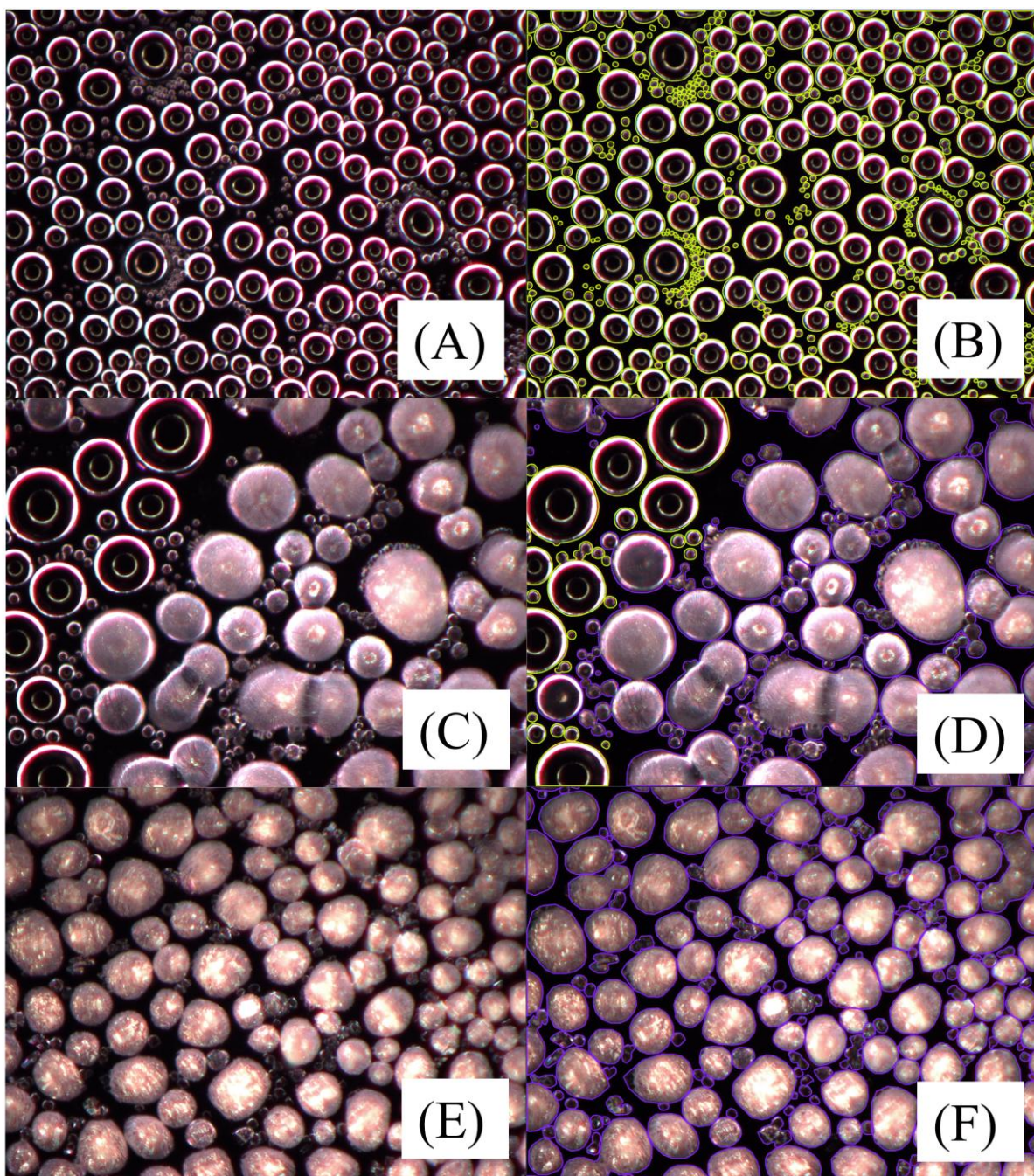


Figure 2.4 Raw images and annotated images of condensation and freezing on a smooth silicon surface that were used for the creation of the neural network model: (A) raw image of condensed liquid water, (B) annotated version of Figure 4A, where yellow indicates liquid water, (C) raw image of water and ice (D) annotated version of Figure 4C, where yellow indicates liquid water and purple indicates ice, (E) raw image of a fully frozen surface, and (F) annotated version of Figure 4E, where purple indicates ice.

Training was conducted for 110 epochs, where an epoch can be defined as one complete pass through the entire training dataset by the model. The dataset was divided into 92% training, 4% validation, and 4% test images. A larger proportion was allocated to the training set due to the limited size of the annotated dataset, ensuring sufficient examples for model learning while retaining independent subsets for validation and final evaluation.

Training and validation losses (box, classification, and objectness) were monitored at each epoch, along with standard performance metrics including precision, recall, and mean average precision (mAP) (Figure 2.5). The model exhibited rapid convergence during the early epochs, with performance saturating after approximately 50–60 epochs, after which mild overfitting in classification loss was observed. The best-performing model checkpoint was selected based on validation mAP.



Figure 2.5:

Training dynamics of the YOLOv11-n object detection model over 110 epochs, showing (top) model performance in terms of mean Average Precision at an IoU threshold of 0.50 (mAP@50) and averaged over IoU thresholds from 0.50 to 0.95 in steps of 0.05 (mAP@50:95), and (bottom) the three loss components used during optimization: box loss (bounding-box regression error between predicted and ground-truth boxes), class loss (multi-class classification error for object categories), and object loss (objectness error for distinguishing object vs. background for each anchor).

2.3.4 Model Uncertainties:

In YOLOv11 [40], the confidence value assigned to each detected object is directly linked to how mean average precision (mAP) is computed for the model [41]. The model first produces a confidence score for every predicted box–class pair, reflecting how sure it is that a given box tightly matches a real object and that the chosen class label is correct [42]. During evaluation, these raw confidences are swept over a wide range of thresholds (from very low to high values), and for each threshold the predictions with confidence above that value are kept while the rest are discarded. At each threshold, the resulting set of detections is compared with the ground-truth annotations to compute precision (how many predicted objects are correct) and recall (how many real objects are successfully found), using an overlap criterion such as intersection over union (IoU). These pairs of precision and recall values form a precision–recall curve for each class [43], and the area under this curve is called the average precision (AP) of that class [44]. Finally, mAP is obtained by averaging these AP values over all object classes, giving a single summary score of how well YOLOv11’s confidence scores, bounding boxes, and class labels work together across different confidence thresholds and IoU settings [45].

Following training, the model achieved a Mean Average Precision at an Intersection over Union (IOU) threshold of 0.50 of 78%, along with a precision of 75% and a recall of 76.5%. Mean Average Precision at an IoU threshold of 0.50 is used to assess the model’s object localization capability by quantifying the degree of overlap between predicted bounding boxes and corresponding ground truth annotations. Under this criterion, a detection is considered correct when the IoU meets or exceeds 50%. A relatively high mAP@0.50 value, approaching unity,

suggests that the model is generally able to produce bounding boxes with substantial spatial agreement relative to the ground truth for a considerable fraction of the evaluated instances, although this metric alone does not fully capture performance under more stringent localization thresholds.

2.4 Results and Discussion

Four trials were conducted for each surface. For all eight trials, the same general behavior was observed. Once the surface cooled below the dew point, small droplets rapidly nucleated on the surfaces. These droplets grew both through coalescence and direct growth. The detailed differences between the droplet growth behavior on the surfaces are explained below. As droplet growth slowed, droplets began to freeze from the edge of the frame as observed previously [27], [39]. The time at which the first droplet freezes in the field of view is denoted as the initial icing time. The freezing front then propagated across the frame, primarily through ice bridging. Once all the drops in the frame are frozen, the test is concluded and the time recorded as the final freezing time.

Figure 6 shows the video of test 1 for the control surface with the results of the model overlaid on the video at three different times. The image on the far left (Figure 2.6A) shows the initial nucleation at $t = 34$ s. The red overlay indicates that the model has detected a water droplet. During the initial nucleation, the model is less successful at recognizing all the droplets in the field of view. It is partially due to the lack of training data for initial nucleation. In the images used in our training data set, there are often over 1800 drops in a frame during the first few seconds of nucleation. During late coalescence, droplet counts range from 450 to 600 drops. The images with all ice typically have 220–250 distinct drops. Therefore, the images of initial nucleation are significantly more time-consuming to annotate.

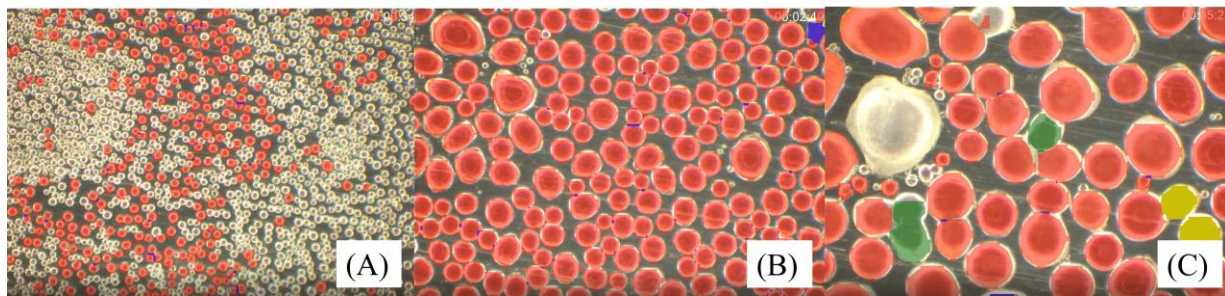


Figure 2.6: Images of the experiment on the aluminum control surface, with the model overlaid at three different times. Red overlay represents that the model has detected a water droplet, blue is overlap between two water regions, green is ice, and yellow is ice/water overlap. The images were taken at (A) $t = 34$ s, (B) $t = 160$ s, and (C) $t = 324$ s.

Additionally, the tiny nature of the droplets makes it difficult to crisply capture in videos, which compounds the difficulty of accurately measuring in the annotation and for the model to recognize. However, the current model's lower identification threshold is currently $4.5\ \mu\text{m}$. The middle image (Figure 2.6CFB) shows the model overlay at $t = 160$ s. Here, the model is much more robust, and it captures nearly every droplet. A few of the smaller droplets (which nucleated in the void between coalesced droplets) were not identified by the model. The blue shaded areas represent water-water overlap where droplets are actively merging. The figure on the far right (Figure 2.6C) shows the test as droplets are beginning to freeze. The green represents ice, and the yellow represents areas of ice-water overlap. When water freezes, its index of refraction changes. Therefore, the ice is more opaque than the liquid water droplets. There are two frozen droplets that were not detected by the model. The image shows that both the droplets have ice bridging from the droplet, which is a clear indication that the drops are frozen. It may also be part of the reason that the ice may not have been detected by the model; additional training images with distinct ice bridging are also needed.

The microtextured surfaces presented challenges to imaging. The ridgeline is significantly taller, $3.3\text{--}9.5\ \mu\text{m}$, than the “smooth” portion, and consequently was out of the focal plane of the microscope when attempting to image droplets in both regions. Experiments were conducted focusing predominantly on the plain region. The condensation started as dropwise in both

regions. As time progresses, the microtextured region appears to become filmwise, while the plain region remains dropwise.

Figure 2.7 shows frames extracted from the video of test 2 for the microtextured surface at three distinct times. The figure on the far left (Figure 2.7A) is during the initial nucleation phase. While the model correctly identifies several droplets, in the first ~ 20 s, it struggles to identify small and tightly packed droplets. As the droplets grow, the model significantly improves droplet identification. Figure 2.8 (on the left) shows a zoomed in view on the microtextured surface of droplet identification for test 2 at 62 s into the test. The model correctly identifies most of the water droplets which are red. It also correctly identifies several areas where droplets are actively merging in blue. A few small and irregularly shaped droplets are missed by the model. Also shown in Figure 2.8 (on the right) is an image where the model incorrectly identified a region of the surface texture as a drop; this incorrect identification also significantly reduces after the initial nucleation phase.

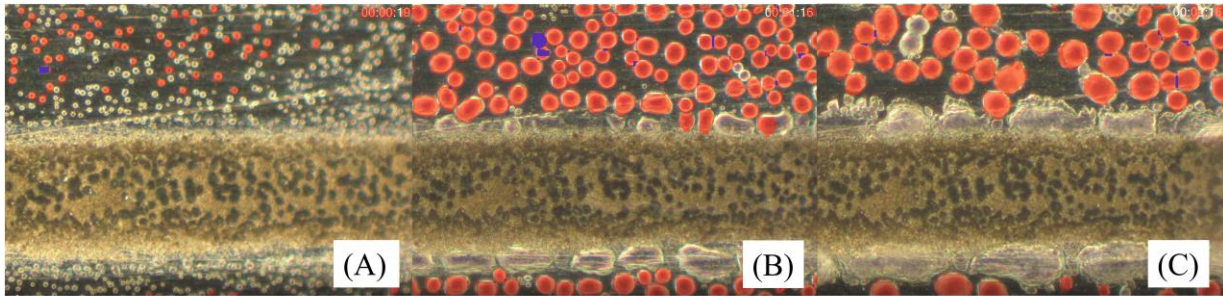


Figure 2.7 Images of the experiment on the microtextured surface, with the model overlaid at three different times. Red overlay represents that the model has detected a water droplet, and blue is the overlap between two water regions. The images were taken at (A) $t = 19$ s (B) $t = 76$ s and (C) $t = 136$ s.

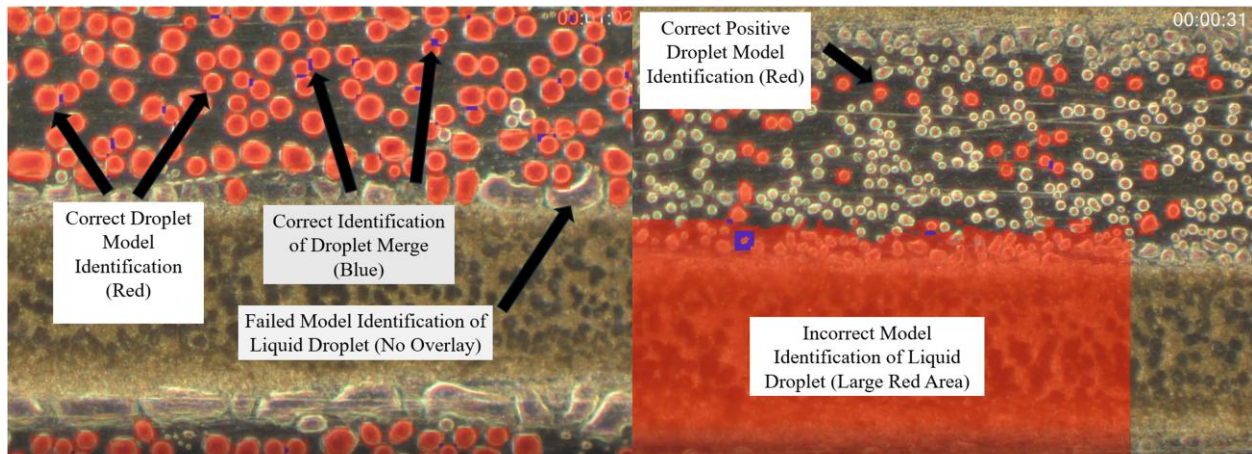


Figure 2.8 On the left is an image of the microtextured surface from Test 2 at $t = 62$ s with the model overlaid. Red overlay represents that the model has detected a water droplet, and blue is the overlap between two water regions. While the model accurately detects most droplets and approximates their correct size, it misses some small droplets and irregularly shaped droplets near the textured edge. On the right is an image from test 3 at $t = 31$ s that incorrectly identified a region of the surface texture as a drop.

Figure 2.9 shows the total droplet count in the total field of view (droplet population) over time for 4 different trials of the control surface. The droplet population rapidly increases due to nucleation on the surface. This initial nucleation is difficult to capture by the model because fewer training images were used in early nucleation. This is due to the significant number of drops and the small droplet size, which is more difficult to annotate. Once the surface becomes saturated with droplets, they grow through direct growth by condensing moisture from the air. As the droplets grow, they begin to coalesce and the total droplet population decreases. The relationship of droplet population with respect to time followed a power law relationship, which has been previously reported in the literature [27], [28], [29]. Using best-fit functions, the power law equation was found for each test. The data collected prior to the model reaching a confidence of $\geq 50\%$ was omitted from this analysis. R values were found to be 0.95 or greater for the control surface. An average exponent of each relationship was found (Table 2.1). The decrease in droplet population during this phase follows the power law with an exponent of -1.5 , as shown in Table 2.1.

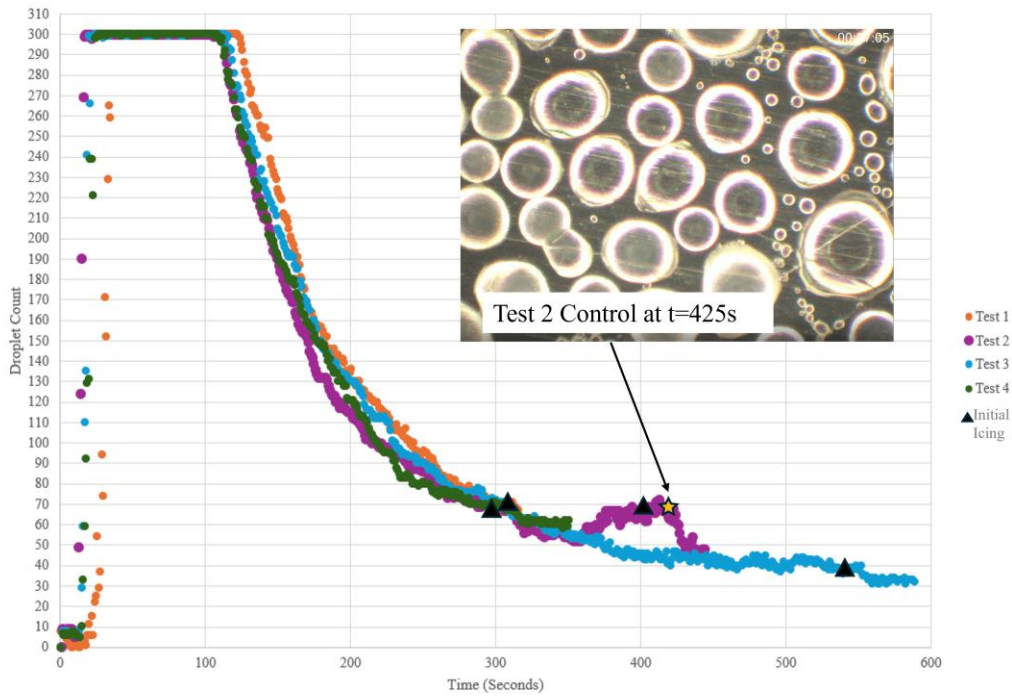


Figure 2.9 Output from the model showing the total droplet count (droplet population) in the field of view over time for the control surface across four different trials. The inset is an image from test 2 at $t = 425$ s denoted with the yellow star on the graph. The black triangles represent the time at which freezing starts in the videos.

Table 2.1 Average power law relationships extracted from the model output for all four trials of the control surface as well as the microtextured surface for the droplet population and the average droplet diameter over time.

Variable	Control	Microtextured
Population (n)	$n \propto t^{(-1.5)}$	$n \propto t^{(-1.3)}$
Diameter (d)	$d \propto t^{(0.63)}$	$d \propto t^{(0.57)}$

Figure 2.10 shows the droplet population over time for four trials on the microtextured surface. The overall behavior of growth and decline of the droplet population is seen in the overall shape of the graph. The increase and decrease of the microtextured surface are different from the

control. However, there is no period of stable population size for either surface. The decrease of the droplet population, which begins around 50 s, also follows a power law but the exponent is -1.2 , which shows a slower population decline due to less coalescence of droplets.

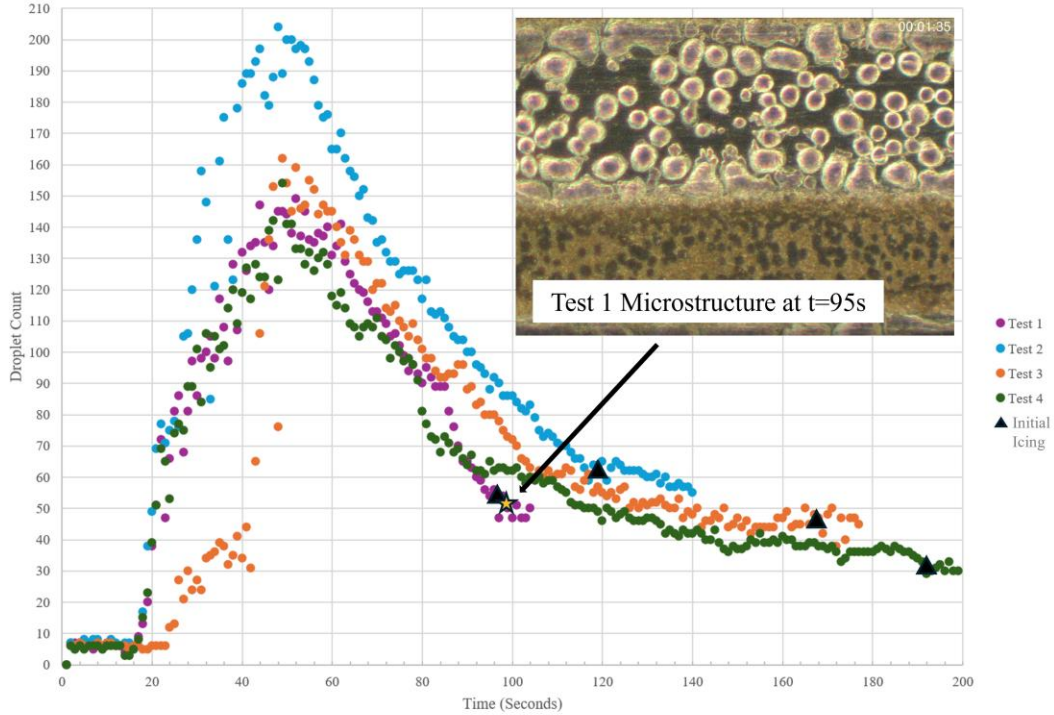


Figure 2.10 - The output from the model showing the droplet count over time across four trials for the microtextured surface. The inset is an image from test 1 at $t = 95$ s denoted with the yellow star on the graph. The black triangles represent the time at which freezing starts in the videos.

For the droplet diameter over time, shown in Figures 2.11 and 2.12, the presence of large droplets in the first few seconds is a model error. It is most likely due to the model being trained on smooth surfaces as well as the lack of training data for the initial nucleation of droplets. Once the model reaches higher confidence levels, the growth of the droplet size matches visual inspection of the videos. Figure 2.11 shows that the droplet diameter also follows a power law curve with an exponent of 0.6, shown in Table 2.1. **Figure 2.12** shows the droplet diameter growth over time on the microtextured surface. The microtextured surface has an average

exponent of 0.57. Previous work has shown that an exponent of 0.5 is expected for diffusion-dominant growth [28].

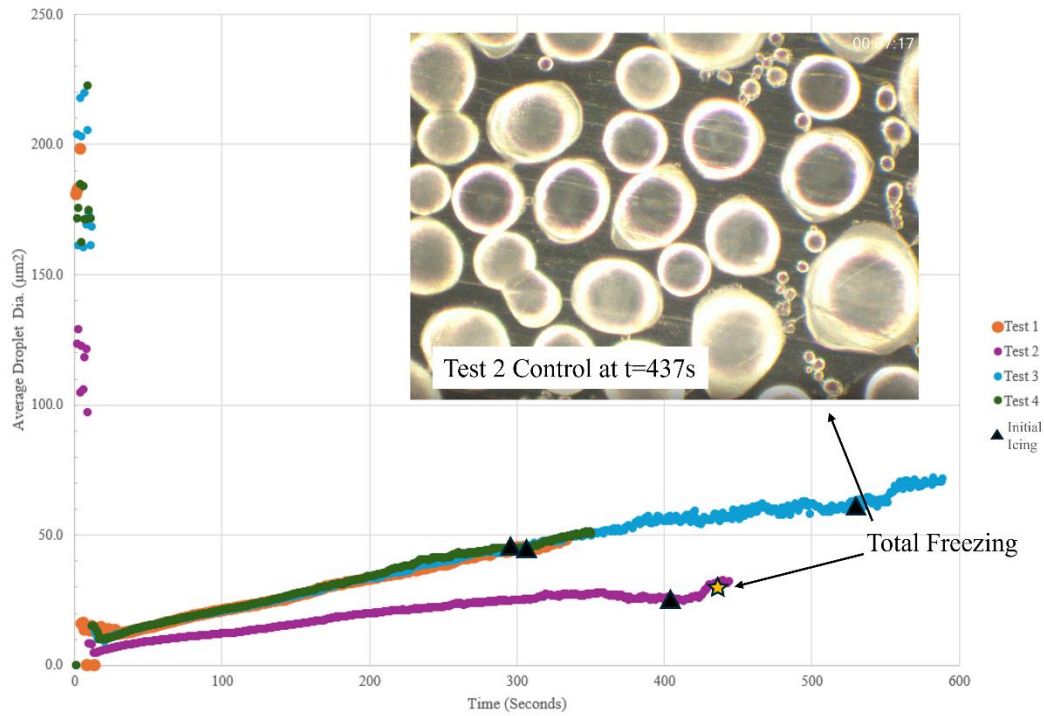


Figure 2.11 Output from the model showing the average droplet diameter for all droplets in the field of view over time for the control surface across four different trials. The inset is an image from test 2 at $t = 437$ s denoted with the yellow star on the graph. The black triangles represent the time at which freezing starts in the videos.

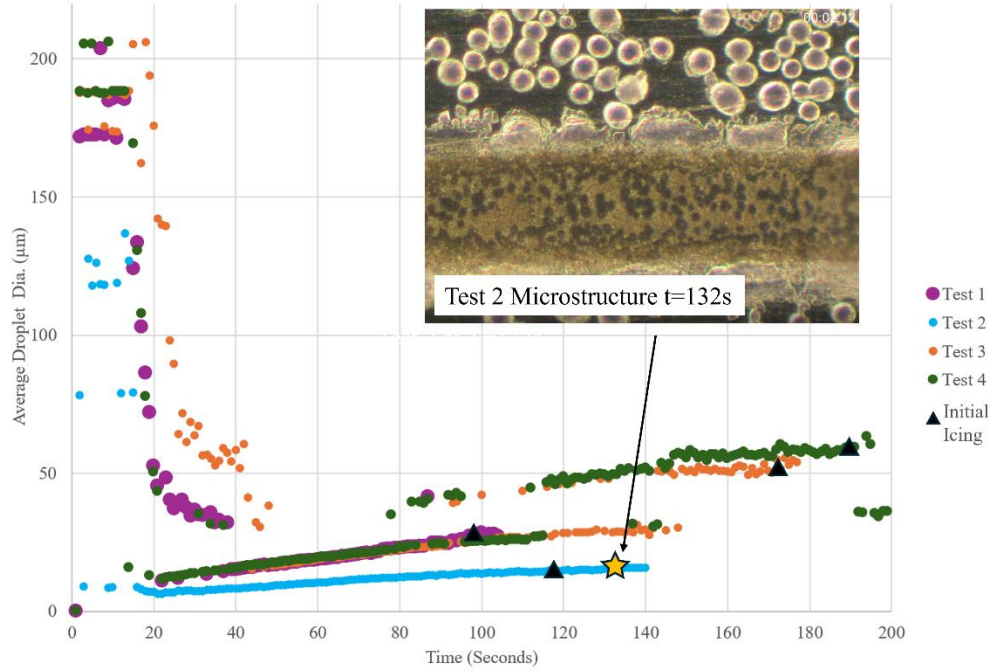


Figure 2.12 - Output from the model showing the average droplet diameter for all droplets in the field of view over time for the microtextured surface across four different trials. The inset is an image from test 4 at $t = 172$ s denoted with the yellow star on the graph. The black triangles represent the time at which freezing starts in the videos.

The modification of the substrate resulted in a measurable change in droplet growth dynamics. Exhibited as a shift in the power law exponent governing droplet radius evolution and population, $R \sim t^\alpha$ [28], [29]. On the unmodified control surface, droplet growth follows a scaling consistent with coalescence-dominated growth, where population grows $n \propto t^{-1.5}$ and droplet diameter grows $d \propto t^{0.63}$ [25], [28]. In contrast, the modified substrate exhibits a smaller exponent for population growth $n \propto t^{-1.3}$ and droplet diameter growth $d \propto t^{0.57}$, indicating an earlier transition to direct condensation. The change in exponents is characteristic of systems where enhanced droplet pinning and reduced mobility prevent coalescence [25], [29]. These results suggest that surface modification alters the balance between vapor deposition and coalescence, thereby shifting condensation dynamics toward faster droplet growth.

We measured freezing time by recording the total time from nucleation to a frozen field of view. Total frosting occurred on the control in approximately 7 min, while the microtextured surface froze completely in 2 min and 20 s on average. Thus, the microtextured surface froze three times faster than the control (Table 2.2). Increasing surface area and greater surface roughness provided by the ridge lines increased droplet pinning and solid–liquid contact area, which stifled their growth and accelerated freezing rates [7], [39]. Solid-liquid contact area and pinning both lowered the energy barrier for heterogeneous nucleation and improved heat transfer from the droplet to the substrate [22], [23]. Faster freezing was not due to an intrinsic change in ice growth rate; it was a result of altered condensation dynamics driven by surface properties. The machine learning model helped establish a direct link between changes in power-law relationships and accelerated icing on the microtextured surface. The change in surface characteristics shifted the condensation behavior from coalescence-dominated growth on the control surface to direct growth on the microstructured surface.

Table 2.2 - Comparison of freezing times for the control and microtextured surfaces for all four trials.

Test	Total Time: Control (sec.)	Total Time: Microtextured (sec.)	Total Time Rate ratio (control/microtextured)
1	334	85	3.9
2	427	115	3.7
2	574	169	3.4
4	343	139.5	1.8
Average	419.5	139.5	3

2.4.1 Neural Network Evaluation

The resulting confidence graphs from the model are shown in Figures 2.13, 2.14. The experimental timeline starts at nucleation and ends at complete freezing. The model’s confidence is reflected by the total number of images annotated at each stage of the process. Due to the large number of hours required to annotate these images, annotation efforts focused on images that show the greatest

variety in droplet growth mechanisms (typically in the middle section of the experiments). The model exhibits higher confidence for smooth surfaces when the average droplet size is approximately 15 μm or greater. Confidence continues to increase and hover around 70% for the microtextured surface or the control until freezing is complete. This trend is due to the greatest number of annotated images being completed for this portion of the experiment. We expect confidence to increase across all parts of the timeline as the data set grows.

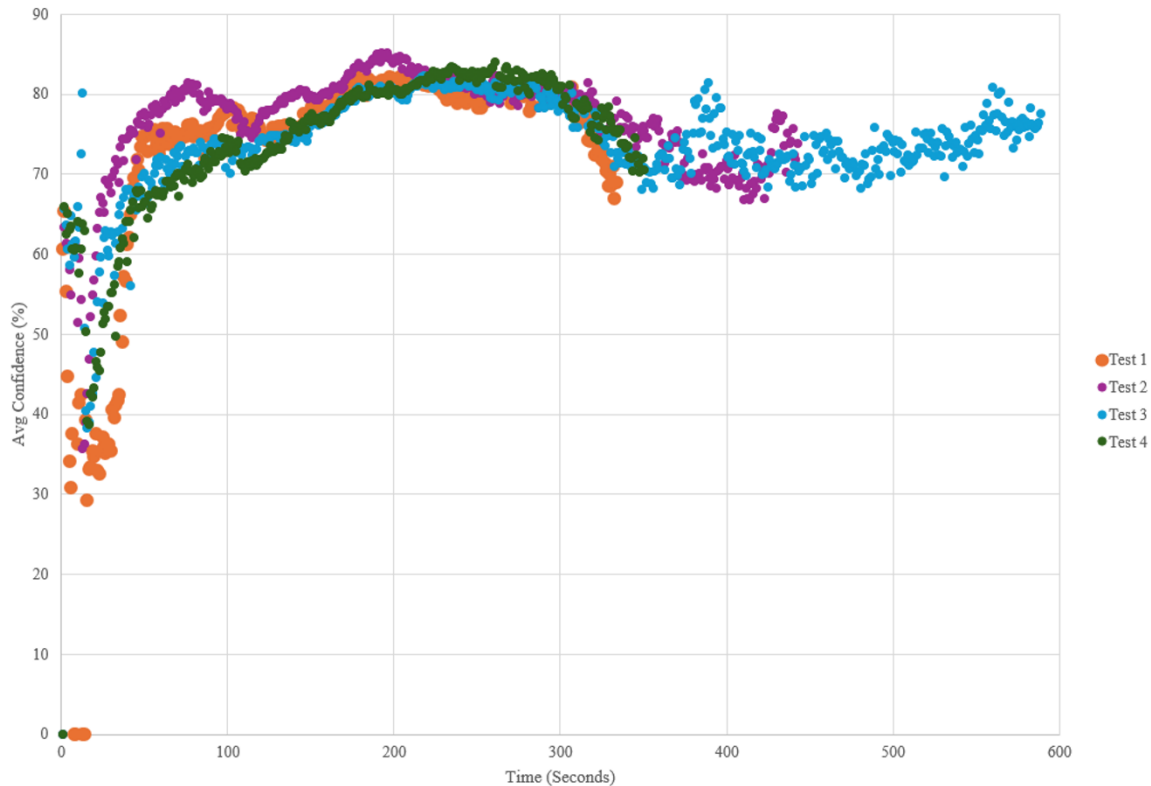


Figure 2.13 - Output of the average model confidence at every second for the control surface across four different trials.

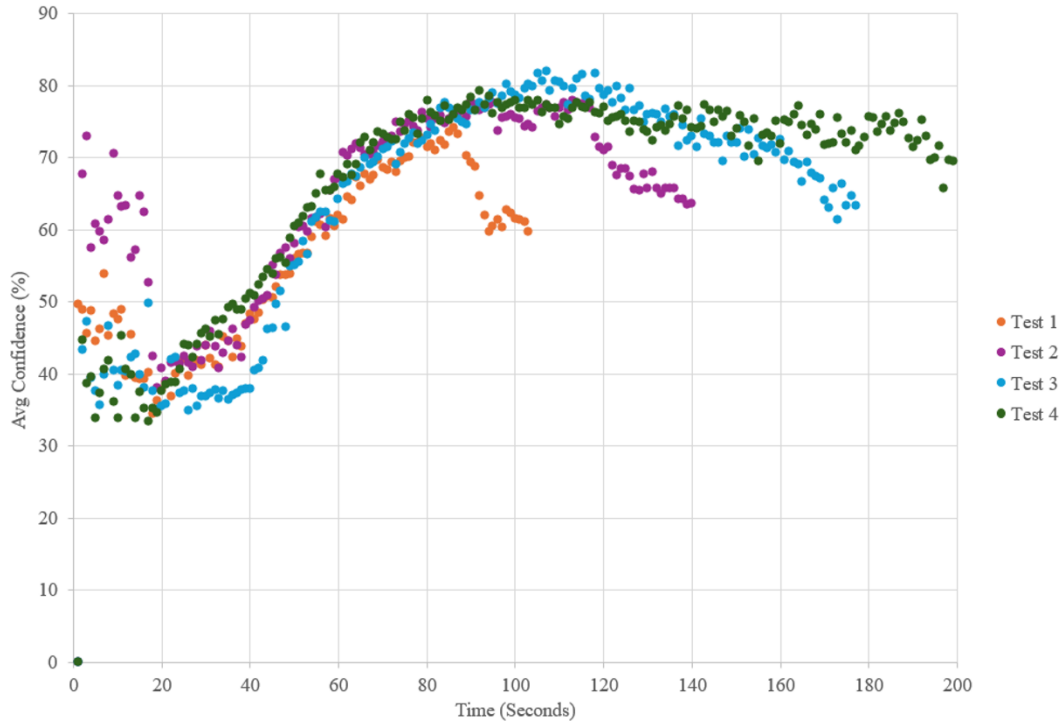


Figure 2.14 - Output of average model confidence at every second for the microtextured surface across four different trials.

2.5 Conclusions

Droplet pinning and coalescence play a significant role in governing freezing behavior. Using the AI neural network model, we observed that condensation exhibits power law behavior in both droplet population and size, regardless of whether the process is dominated by coalescence or dropwise condensation. For the control surface, coalescence was more prevalent, because of the higher exponent in droplet growth and the decrease in exponent for the droplet population. This matches prior literature that shows structures pinning droplets prevent coalescence. Results from the microtextured sample indicate that increased surface topography enhances droplet pinning, thereby decreasing freezing time even though ice bridging dominated the freezing front propagation on both surfaces.

Rather than tracking a single droplet, we analyzed the full observed droplet field, capturing both population dynamics and the evolution of droplet diameters over time. This field-level

perspective yields stronger statistical confidence and a more comprehensive characterization of droplet behavior during condensation and freezing. These results motivate further investigation of pinning effects across a broader range of engineered surfaces and substrate materials to evaluate the generality of the observed trends. Beyond condensation, the YOLO model and AI workflow can be adapted to related multiphase phenomena by adjusting the observation and event definitions to the underlying physics. Promising extensions include spray-pattern characterization and bubble-nucleation analysis during the boiling phase. Further progress is also expected by integrating neuro-symbolic AI approaches to improve the explainability of results for surface types, enhance the interpretability of inferred mechanisms, and better support generalizations.

Chapter 3 : ⁴Influence of MoS₂ Flake Syntheses (CVD and ME) on Condensation Dynamics and Frosting

3.1 Introduction

Molybdenum disulfide (MoS₂) is an inorganic compound that exists in nature in the mineral molybdenite. Its crystals have a hexagonal layered structure that is similar to graphite [33].

MoS₂, like graphite, is used as a dry lubricant and has semiconductor properties [33].

Molybdenum disulfide exhibits a complex, tunable wetting behavior that is highly dependent on its environment, number of layers, and surface defects [34]. The wetting properties of MoS₂ may be useful in real-world applications where water accumulation, condensation, or icing may affect performance. These applications include: heat exchangers, condensers, refrigeration systems, aerospace surfaces, electronics cooling, and other systems. However, its ability to serve as a surface coating to control condensation and frost behavior remains an area worthy of further study. If MoS₂ coatings can be shown to affect condensation and icing mechanisms, then this may provide insights into future frost-control or anti-icing surface designs.

The objective of this research is to examine how MoS₂ flake synthesis methods influence condensation and frost formation on silicon substrates. This study compares MoS₂ surfaces produced by two different methods, chemical vapor deposition (CVD) and mechanical exfoliation (ME), with an uncoated silicon wafer as the control surface. The work evaluates: wetting behavior, contact angle, droplet population, average droplet diameter, wetted surface coverage, freezing time, and freezing mechanisms. These variables are gathered utilizing a high-magnification video for analysis by a custom neural-network vision-based model.

3.2 Experimental Apparatus

The experiments presented in Chapter 3 utilize the experimental apparatus described in Section 2.3 Methods. The experiments in Chapter 3 utilize the same experimental procedure and data collection process as described in Section 2.3.2 Operational Procedures.

^{4 4} Portions of this chapter were published in: Turner, Jane C., Aryan Singh Dalal, Hande Küçük McGinty, Melanie M. Derby, and Amy R. Betz. "Examining condensation and freezing behavior on a laser-patterned metallic surface using an AI neural network model." *Frontiers in Thermal Engineering* 6 (2026): 1808591.

3.3 Sample Fabrication

In this experiment, we examined the condensation and frost formation of moist air on molybdenum disulfide (MoS_2) flakes on a silicon wafer substrate. The flakes were synthesized onto the silicon wafers via two different methods: chemical vapor deposition (CVD) and mechanical exploitation (ME). These samples were prepared by Dr. Gurpreet Singh's laboratory group at Kansas State University.

3.3.1.1 Producing MoS_2 via CVD

MoS_2 is grown on the Si surface via CVD, as described by Owiredu et al. [37]. The MoS_2 samples used in these experiments were produced by Dr. Singh's lab group. After multiple washes and sonication to ensure optimal cleanliness, the Si wafer was placed on top of a ceramic boat containing MoO_3 , which was subsequently placed into a quartz tube. Accompanying the wafer- MoO_3 boat in the tube was an additional ceramic boat containing sulfur. The two boats were separated by 20 cm inside the tube. The quartz tube was then placed into a high-temperature furnace, with the MoO_3 and wafer end placed in the higher temperature zone than the sulfur end. The tube was then purged three times with ultra-high purity argon gas and sealed. The furnace was then raised to 850°C at $13^\circ\text{C min}^{-1}$. After maintaining the temperature at 850°C for 10 min, the furnace was cooled to room temperature with an argon flow rate of 50 sccm. During cooling, the argon flow over the sulfur pile draws sulfur molecules across the wafer- MoO_3 boat. The sulfur molecules first reach the MoO_3 pile, mix as gases, then are deposited as MoS_2 flakes as the imbued argon gas flows over the waiting Si wafers. The resulting S:Mo ratio was noted to be between 1.8 and 1.9 [46], [47], [48].

3.3.1.2 Producing MoS_2 via ME

Dr. Singh's group produced additional samples using mechanical exfoliation onto the silicon substrate, as described by Owiredu et al. [37]. A small amount of natural bulk crystals of MoS_2 were adhered to Nitto brand tape - a low-residue tape. The tape was repeatedly folded and separated to obtain thin MoS_2 flakes. The Si wafer was sonicated in an acetone bath, etched through a reactive-ion etching process, and cleaned with isopropanol. The flake-imbued tape was then placed onto the prepared silicon wafer and gently rubbed with the tip of a cotton swab. [37].

3.3.2 Surface Characterization

3.3.2.1 Optical Images: MoS_2 produced via CVD and ME

Surfaces were imaged on a Leica DVM2500 microscope, on which the experiments were performed. There were challenges in imaging the MoS_2 surfaces. With the room lights on, it was found to be an impossible image, as the surfaces were imaged as sooty black. After turning off the room lights and setting the microscope's built-in light to 10% illumination, it was possible to clearly see both surface types. Figure 3.1 shows the MoS_2 - CVD at two different resolutions. The first, Figure 3.1 A, shows a speckled background reminiscent of a star field at 1000X. The same sample at 2500x, Figure 3.1B, shows the light gold hexagons of the molybdenum disulfide. However, as can be seen in the graphic in 3.9, the flakes can reflect back a number of colors, including a glacial blue when droplets are present. In Figure 3.2A, under 200x, the large natural flakes of MoS_2 can be seen as a gold smudge. It is assumed that the silver splotches are some type of surface defect. The gold smudge resolves into a highly geometric archipelago in Figure 3.2B at 600x.

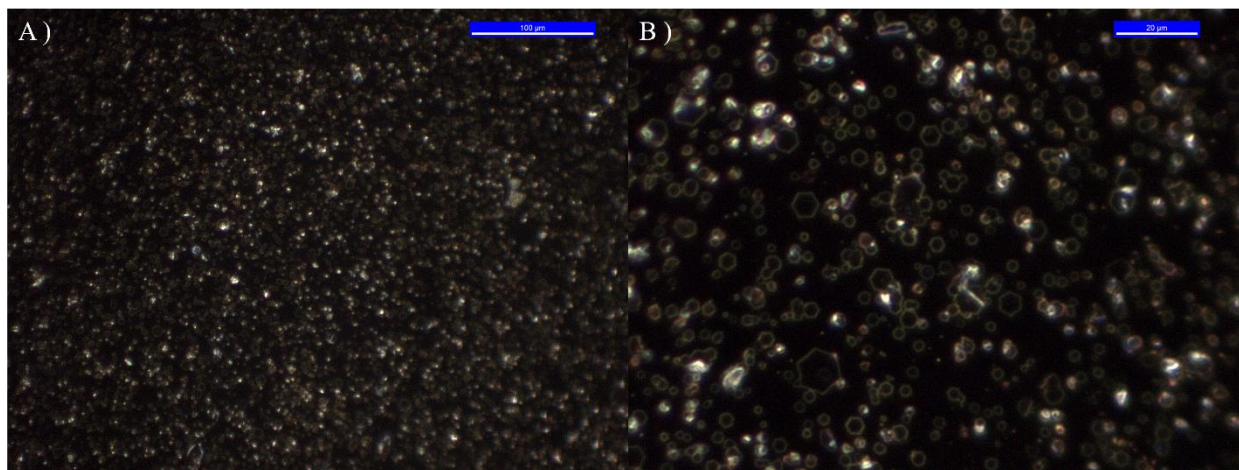


Figure 3.1 MoS_2 -CVD: A) 1000× Magnification MoS_2 flakes are barely visible. B) 2500× Magnification in individual flakes are distinguishable.

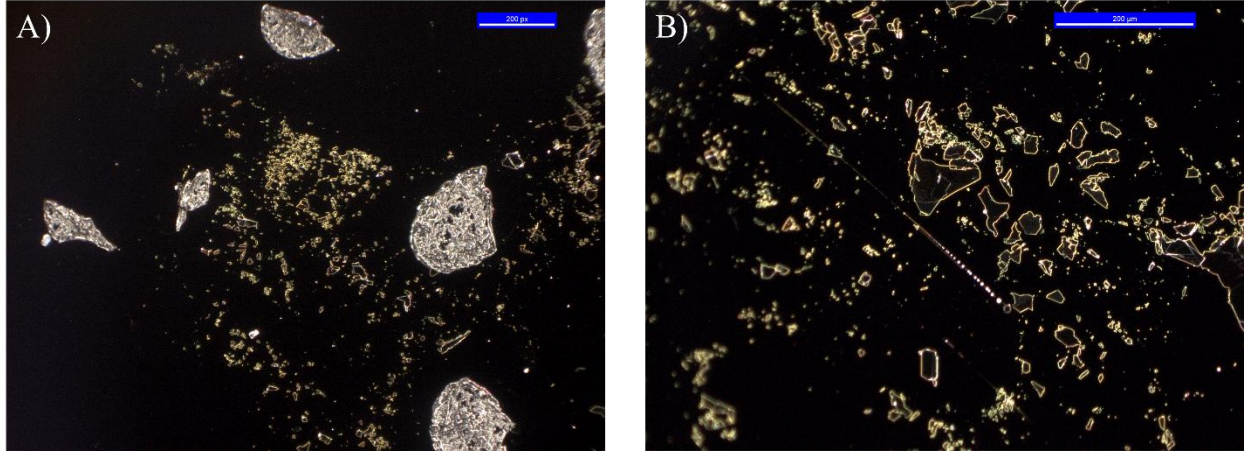


Figure 3.2: A) A 200 $\times$ image of MoS₂-ME surface and B) 600 $\times$ image of MoS₂-ME flakes.

3.3.2.2 Contact Angle Measurements

Contact angles affect condensation frosting and subsequent freezing, both surfaces were characterized using the technique described in Section 2.3.1. Due to the uneven distribution of both MoS₂-CVD and MoS₂-ME coatings on their Si substrates, each sample surface into four quadrants and measured the contact angle eight times in each section. Then, the thirty-two data points were averaged. Average values are reported in Table 3.2. The control was only sampled in one location. The higher contact angle of the MoS₂-CVD is likely due to a more uniform MoS₂ coating in the manufacturing process. As seen in Figure 3.1, the distribution of MoS₂ flakes is homogeneous, while in Figure 3.2, the MoS₂ remains in large chunks that are more isolated.

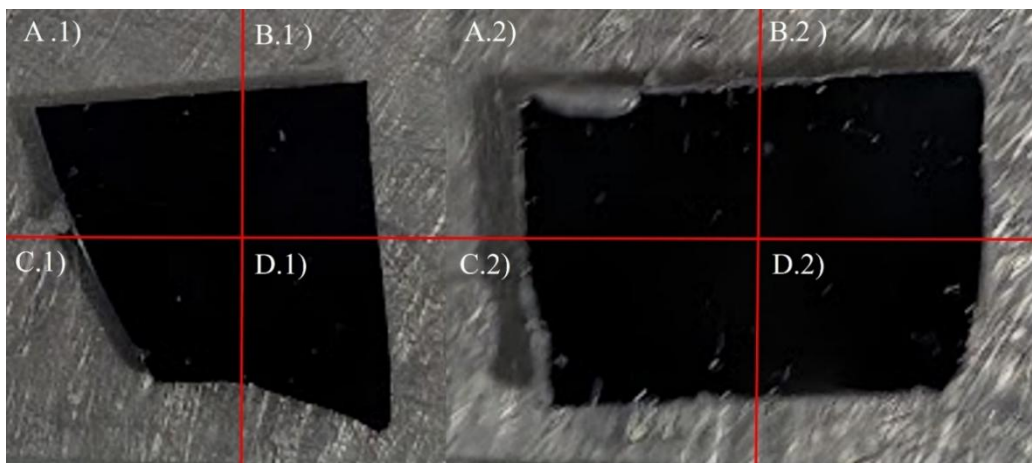


Figure 3.3 MoS₂ - ME and CVD Wetting Map: (Left) MoS₂-ME - A.1) 1st Quadrant, B.1) Second Quadrant, C.1) 3rd Quadrant, D.1) 4th Quadrant. (Right) MoS₂-CVD – A.2) 1st Quadrant, B.2) 2nd Quadrant, C.2) 3rd Quadrant, D.2) 4th Quadrant.

Table 3.1 : Silicon Substrates Average Contact Angle Measurements

Location	Test	Control Before	Control After	MoS₂-ME	MoS₂-CVD
Loc. 1	1	79.56	90.55	92.03	107.52
	2	83.98	93.41	91.13	106.7
	3	82.35	88.01	95.93	101.78
	4	78.07	93.22	93.6	103.49
	5	88.03	92.21	94.4	95.37
	6	78.84	93.38	97.56	102.98
	7	83.34	91.53	95.79	101.746
	8	89.98	88.36	91.8	104.49
Loc. 2	1			91.76	99.5
	2			95.67	102.49
	3			93.84	102.04
	4			92.35	100.59
	5			87.89	107.2
	6			89.66	104.04
	7			89.98	105.01
	8			87.05	105.62
Loc. 3	1			95.72	105.1
	2			102.1	107.56
	3			93.41	109.57
	4			95.91	101.4
	5			94.7	109.42
	6			98.9	99.76
	7			97.46	106.57
	8			86.84	108.71
Loc. 4	1			90.36	106.15
	2			93.67	103.42
	3			88.19	103.47
	4			93.09	107.49
	5			91.63	104.67
	6			88.5	103.78
	7			86.96	106.12
	8			99.12	106.3
Average		83.02	91.33	92.74	104.38
Standard Dev.		±4.01°	±2.04°	±3.78°	±3.1°

These values were found empirically using a goniometer. It was suspected that a natural oxide layer would form on the control wafer. It was felt necessary to only sample the control in one location as it was assumed the oxide layer would grow evenly across the control surface. A before-and-after contact angle was taken accordingly. The MoS₂-ME and MoS₂-CVD wetting properties were collected prior to testing.

3.4 Experimental Procedure

3.4.1 Condensation and Freezing Procedure

These experiments primarily use the experimental procedure reported in Section 2.3.2 *Operational Procedures*. The variations used in this experiment consist of the use of a single Surface Thermocouple with Self-Adhesive Backing (Omega - SA1-J-72). Due to the extremely thin nature of the samples and their diminutive overall size (less than 10 mm x 10 mm), it was not appropriate to place the thermocouple beneath the sample. As this may have caused greater thermal resistance between the sample and the Peltier cooler. It was decided to place the thermocouple adjacent to the sample (Figure 3.4) with Omega High Temp & Conductive Paste (OT-201-16, thermal conductivity of 2.3 W/mK). The Peltier cooler was set to -5° C. The thermocouple showed a variation of surface temperature $-4.18 \pm 0.45^{\circ}\text{C}$, $-4.695 \pm 0.10^{\circ}\text{C}$, $-3.85 \pm 0.33^{\circ}\text{C}$, for the control, MoS₂-CVD, and MoS₂-ME respectively. Ambient air conditions were 19-21° C and 45-51% RH. The experiment concluded when the full field of view appeared frozen, as indicated by a phase change due to the droplet's opacity.

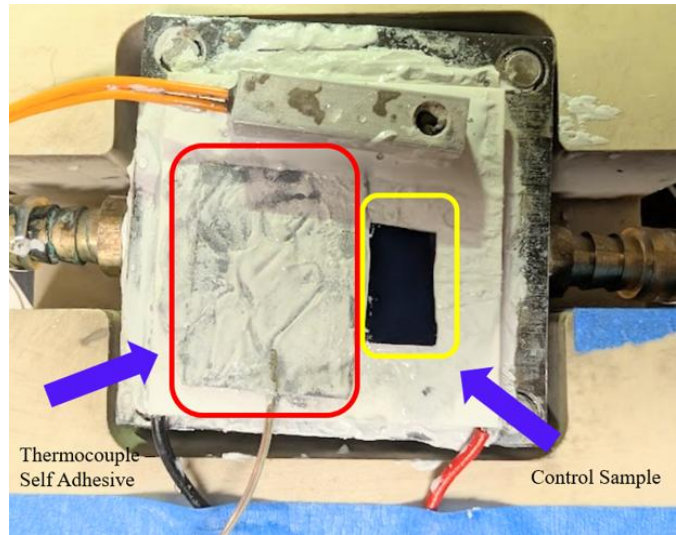


Figure 3.4 : Figure 3.5 : Top view of the thermocouple and sample surface arrangement used with all surfaces.

3.5 Neural-Network Image Analysis

3.5.1 Data Processing

The experiment videos were decimated to a frame rate of 1 frame per second (FPS) to make file sizes manageable for image processing. An additional 100 images of icing on a Si wafer were annotated and added to the training set prior to the processing of the experimental data obtained in this chapter. All other model architecture and training were the same as in section 2.33.

3.5.2 Droplet Detection Outputs

Overall, droplet detection of population and size was strong across surface types, though model accuracy for phase change remained unreliable. Model confidence reached 75% or greater when the average droplet size was 10 μ m or more for all surfaces. On the control surface, a significant improvement was observed in phase change detection. The model correctly identifies the ice 85% of the time as observed by a human. This is likely because a large number of the model's training image set are smooth silicon wafers. In the test overlay of the control, we see a detection of all droplets at approximately $t = 130$ seconds; the average droplet size is 23 microns, and the confidence level is 80% (Figure 3.5C). The model continues to mask every droplet until freezing starts. It is observed that while there is masking of most droplets during this period, the model struggles to identify droplets after multiple droplets have frozen together (Figure 3.5D). Also, after freezing initiates, it has poor identification of what is ice (green), water (red), and ice water merging events (yellow).

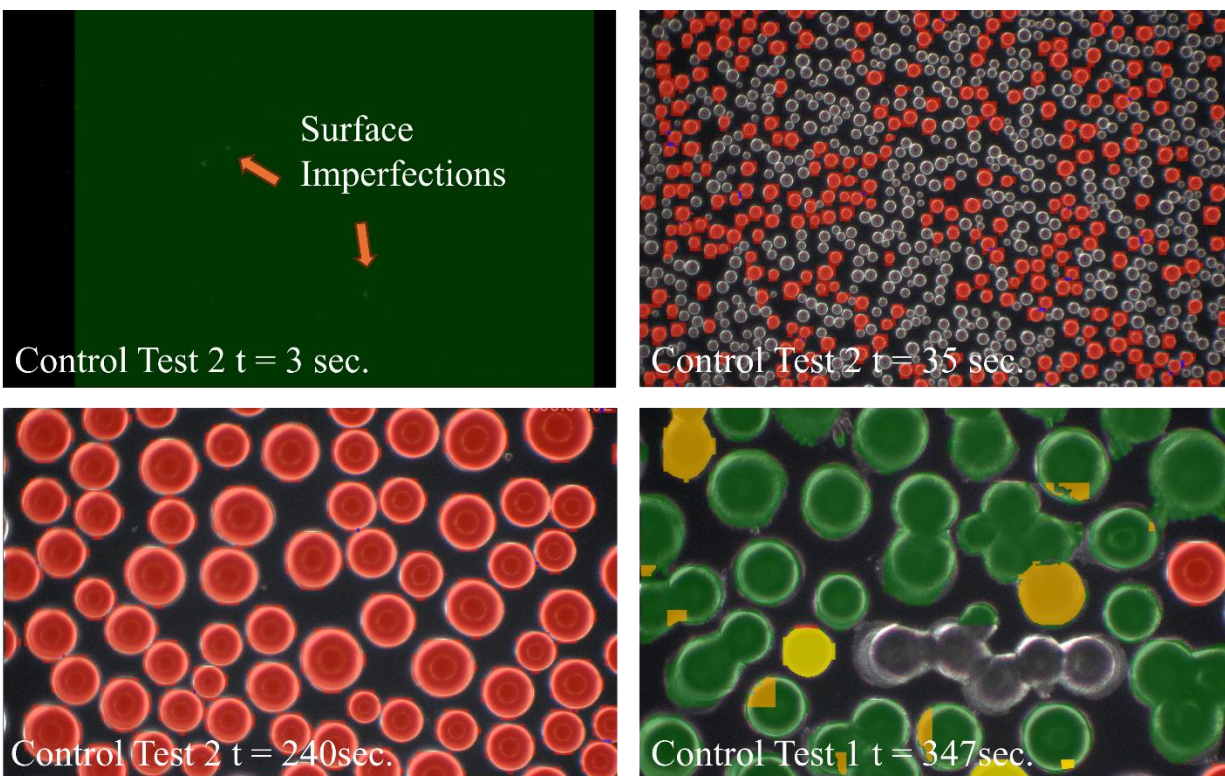


Figure 3.6: Vision model masking of various control tests. A) Small surface defects cause the model to assume that the entire surface is frozen (green box) in the early stages. Can be seen as large blips early in the diameter graph (Figure 3.10). B) Incomplete masking of droplets in the early stages of the experiment. Average Dia $9.54\ \mu\text{m}$ C) Highly accurate masking of liquid droplets. D) Model does well masking and identifying the correct phase of the water. However, the model struggles to identify all the grouped droplets that have frozen together.

The model showed the lowest accuracy in droplets and phase change with MoS_2 –CVD. It is possible that this is due to the multifaceted, multicolored nature of these small, regular flakes in the resulting images. Similar to early control and test, the model identifies newly nucleated droplets as a single large ice field (Figure 3.6A). At $t = 72\ \text{s}$, the average droplet diameter is $14\ \mu\text{m}$; the complex background makes droplet identification difficult (Figure 3.6B). As time progresses, the resolution of drop identification improves rapidly with increasing droplet diameter (Figure 3.5C). However, as shown in Figures 3.5C and 3.5D, phase-change identification on this surface remains limited.

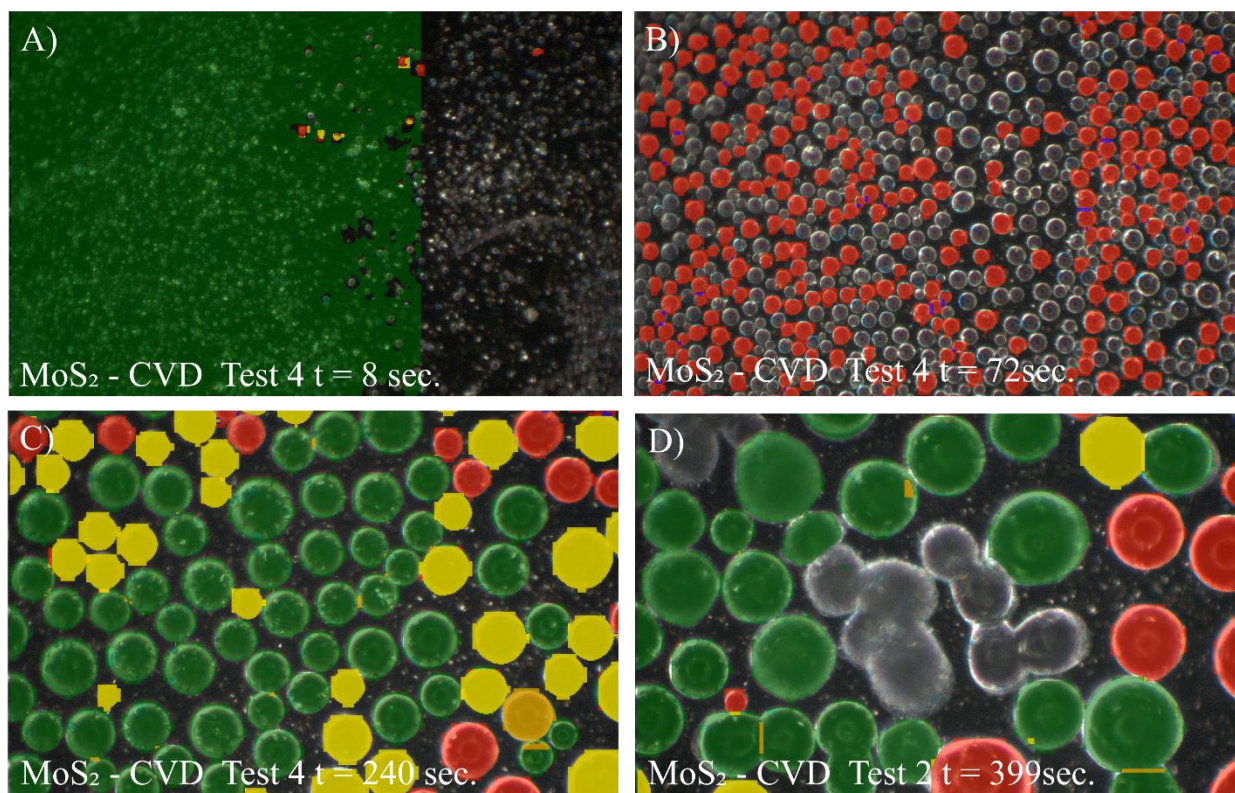


Figure 3.7: MoS₂ – CDV Vision model masking on various tests. A) Shows identification error of early droplet field as ice. B) shows a struggle to identify droplets against a novel, multi-faced background. C) The Model identifies a liquid droplet field as mostly ice (green) far before freezing occurs. D) Ice field with partially accurate identification of ice, but also failure to identify large multi-drop sections.

The results of the model evaluation were very impressive in both droplet identification and droplet phase detection. As suspected, the model incorrectly identified the large MoS₂ flakes as various phases of water in the early stages of the experiment (Figure 3.7A). The model was able to track the noncircular droplets well, even at the smallest edge of the model's reliable identification resolution size (Figure 3.7B). As time progresses, the model very seldom includes flakes in its droplet count, even though the flakes remain clearly visible in the background (Figure 3.7C). Lastly, the accuracy of phase change identification for the mechanically exfoliated surface is comparable to that of the control. Even though this surface produced exceptionally wide and frilly dendrites (Figure 3.7D).

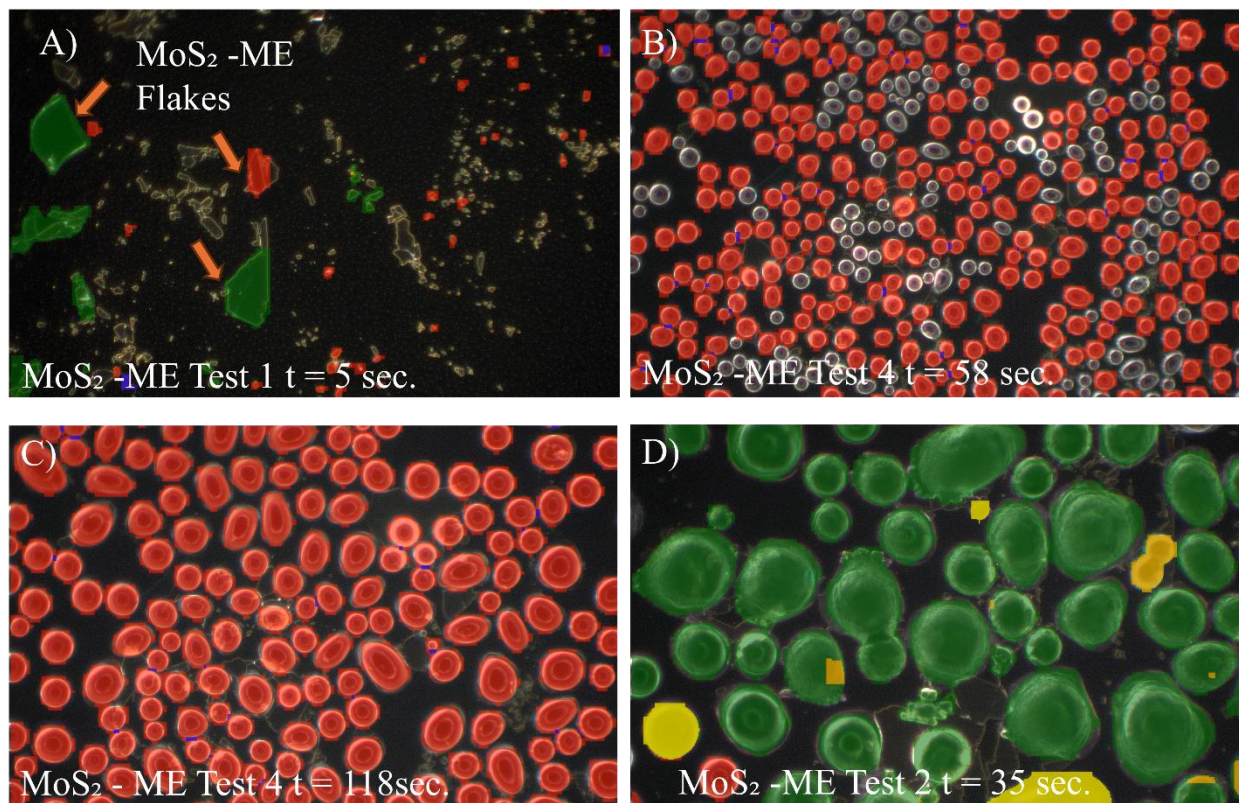


Figure 3.8: MoS₂ – ME Vision model masking on various tests. A) Mistaken identification of MoS₂ – ME flakes. B) Masking at t = 58 Sec average droplet diameter 16 μ m. C) Masking at t = 118 seconds, average droplet diameter 25 μ m. D) Masking of frozen droplet field with high phase state accuracy.

3.5.3 Model Evaluation

Despite shortcomings in early droplet detection (i.e., < 10- μ m-diameter droplets) and late-phase change, the model remains highly accurate in capturing droplet populations and diameter. During the initial nucleation, the model is less successful at recognizing all the droplets in the field of view. It is partially due to the lack of training data for initial nucleation, but also due to the incredibly small nature of the phenomenon being observed. The model reaches 75% accuracy by the time the average droplet diameter reaches 10 μ m or 78 pixels. In the images used in our training data set, there are often over 1800 drops in a frame during the first few seconds of nucleation. During late coalescence, droplet counts range from 450 to 600 drops. The images with all ice typically have 220–250 distinct drops. Therefore, the images of initial nucleation are significantly more time-consuming to annotate. Accurate phase change identification is still a

challenge. Mixed water-ice images and all ice images still make up less than a third of the annotated data set. This area of the model is expected to improve with increased annotations to mixed water-ice and all ice images.

3.6 Results

Six trials were conducted for each surface. While the same general behavior was observed over the procedure, nucleation to freeze each surface presented distinctly different patterns of behavior. There are variations in droplet size, population, shape, freezing behaviors, and coalescence rates. Once the surface cooled below the dew point, small droplets rapidly nucleated on the surfaces. Droplets on all surfaces grew both through coalescence and direct growth. The detailed differences between the droplet growth behavior on the surfaces are explained below. As droplet growth slowed, droplets began to freeze from the edge of the frame as observed previously (Bohm et al., 2018; Haque et al., 2018). The time at which the first droplet freezes in the field of view is denoted as the initial icing time. The freezing front then propagates across the frame, primarily via ice bridging, though some cascade behavior was observed in certain tests. Once all the drops in the frame are frozen, the test is concluded, and the time is recorded as the final freezing time.

The three surfaces investigated (control, MoS₂ - CVD, and MoS₂ - ME) all present different overall surface textures, geometries, and consequently, different wetting behaviors. The contact angles in Table 3.2 vary between the surfaces. The Si control wafer is a mirror-smooth polish. The CVD is like a layer of leaves in the fall, stacked on top of each other with small depressions, but no single leaf is sticking up and causing great obstructions to movement. If one ran a hand over the leaves, one would feel very small changes in height where the leaves overlapped, but no great differences. Lastly is the mechanically exfoliated sample. This substrate's texture is like a topographical map of the plains and plateaus of Monument Valley, UT. Smooth glass-like surfaces are interrupted by islands of molybdenum disulfide, stepped and flaked like a piece of crumbling shale, leading up to a plateau of MoS₂.

3.6.1 Power-Law Values

Surface characteristics greatly impact many key aspects of dropwise condensation, such as populations, droplet growth rates, growth mechanisms, and heat transfer rates, as manifested in freezing behavior. [24] [25], [26]. Power-law relationships describe how many fundamental aspects of condensation evolve with time. Beysens and Knobler studied condensation on glass slides and directly showed that condensation on nonwetting glass produces droplet growth where isolated droplets scale as $R \sim t^{0.23}$ and the average droplet population scales as $R \sim t^{0.75}$. The difference in growth rates is due to coalescence-driven growth in a large population. Quéré's review explains that roughness and wetting state determine whether a surface favors film or dropwise formation. Roughness can also influence droplet growth, pinning, or wicking, affecting the time-scaling regime [24]. In 2002, Rose et al presented a comprehensive review of previous condensation and heat transfer experiments. Primarily on industrial steam. It was concluded that dropwise condensation gives much higher heat transfer than filmwise condensation. Confirming the Le Fevre-Rose Theory of heat transfer during dropwise condensation, a relationship that also takes the form of t^α .

All test surfaces followed the expected power law trends. The average power-law exponents in Table 3.3 show that droplet population decreased over time for all surfaces, while average droplet diameter increased over time. Indicating that condensation growth was governed by droplet coalescence. Once the sample surface was saturated with droplets, the population exponent became negative as droplet diameter increased. The order of the slowest population decline to fastest is as follows: control surface $t^{-0.906}$, MoS₂ - CVD $t^{-1.00}$, and was strongest for MoS₂ - ME $t^{-1.349}$. This pattern was not repeated in the growth rate. With the diameter exponents as follows: MoS₂-CVD $t^{0.731}$, Control $t^{0.688}$, and MoS₂ - ME $t^{0.630}$. The high R^2 values, suggest that the power-law model describes the droplet-growth behavior well across the tested surfaces.

Table 3.2: Average Power-Law Values (α)

Variable	Control	R ²	MoS ₂ - CVD	R ²	MoS ₂ -ME	R ²
Population						
(n)	$t^{-0.906}$	0.922	$t^{-1.00}$	0.947	$t^{-1.349}$	0.947
Diameter						
(d)	$t^{0.688}$	0.928	$t^{0.731}$	0.630	$t^{0.630}$	0.998

3.6.2 Droplet Population

The maximum population (Table 3.3) from least to greatest is the ME, the control, and the CVD. With an average population of 1170, 1510, and 1753 droplets. The power law shape of the population graphs is as expected from Rose et al. A steep slope in the first 50 seconds shows that all samples reach their peak population. Showing that the population is growing as nucleation and coalescence commence. After reaching max surface coverage, the curve descends as the droplet pollution starts shrinking. This negative curve represents droplets merging together as the average diameter increases. The power laws for each test were calculated using a best-fit function in Excel. The alpha value was averaged among the tests and is reported in Table 3.3.

Table 3.3: Maximum Droplet Population (*n*) of Surfaces

Test	Control	MoS ₂ - CVD	MoS ₂ - ME
1	1995	1	1992
2	1271	1575	940
3	1652	1904	912
4	1467	1802	1083
5	1280	1545	933
6	1392	1939	1162
Average	1510	1753	1170

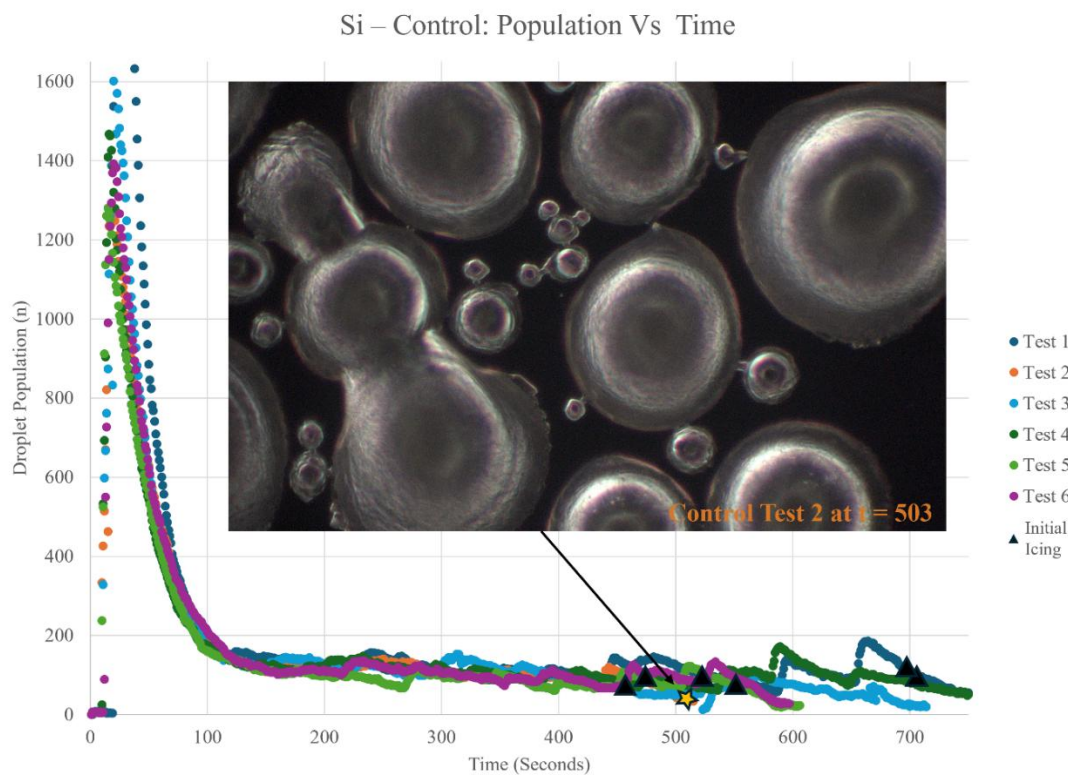


Figure 3.9 : Si – Control Population (n) versus time

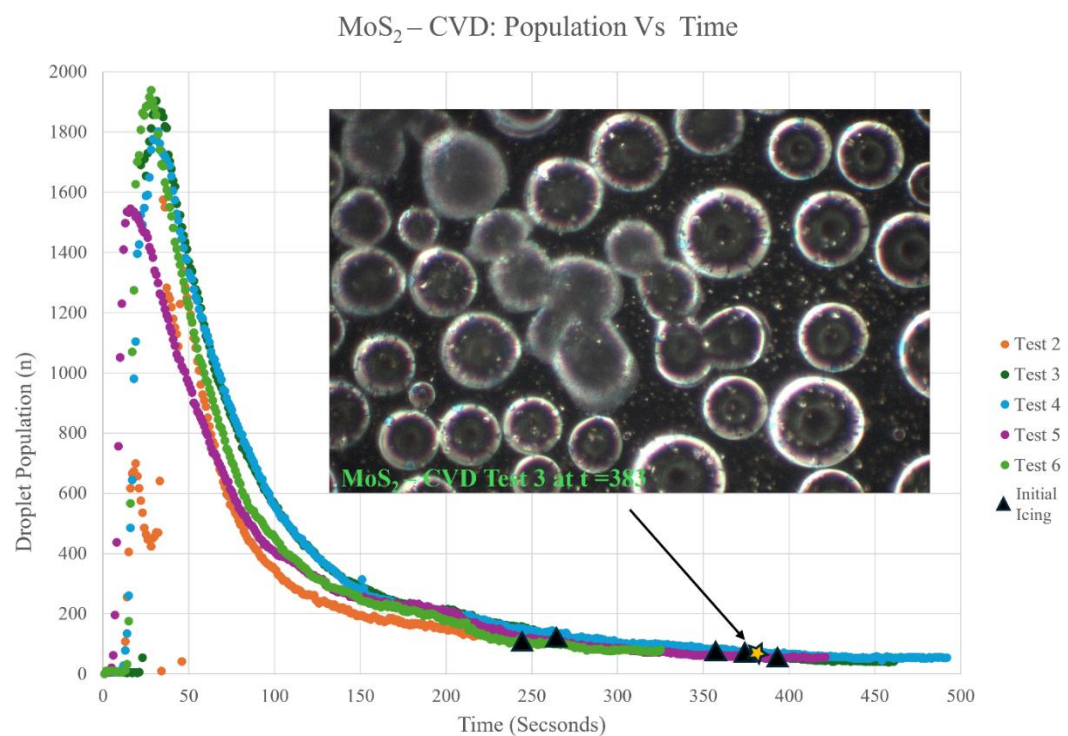


Figure 3.10: MoS₂ - CVD Population (n) versus time.

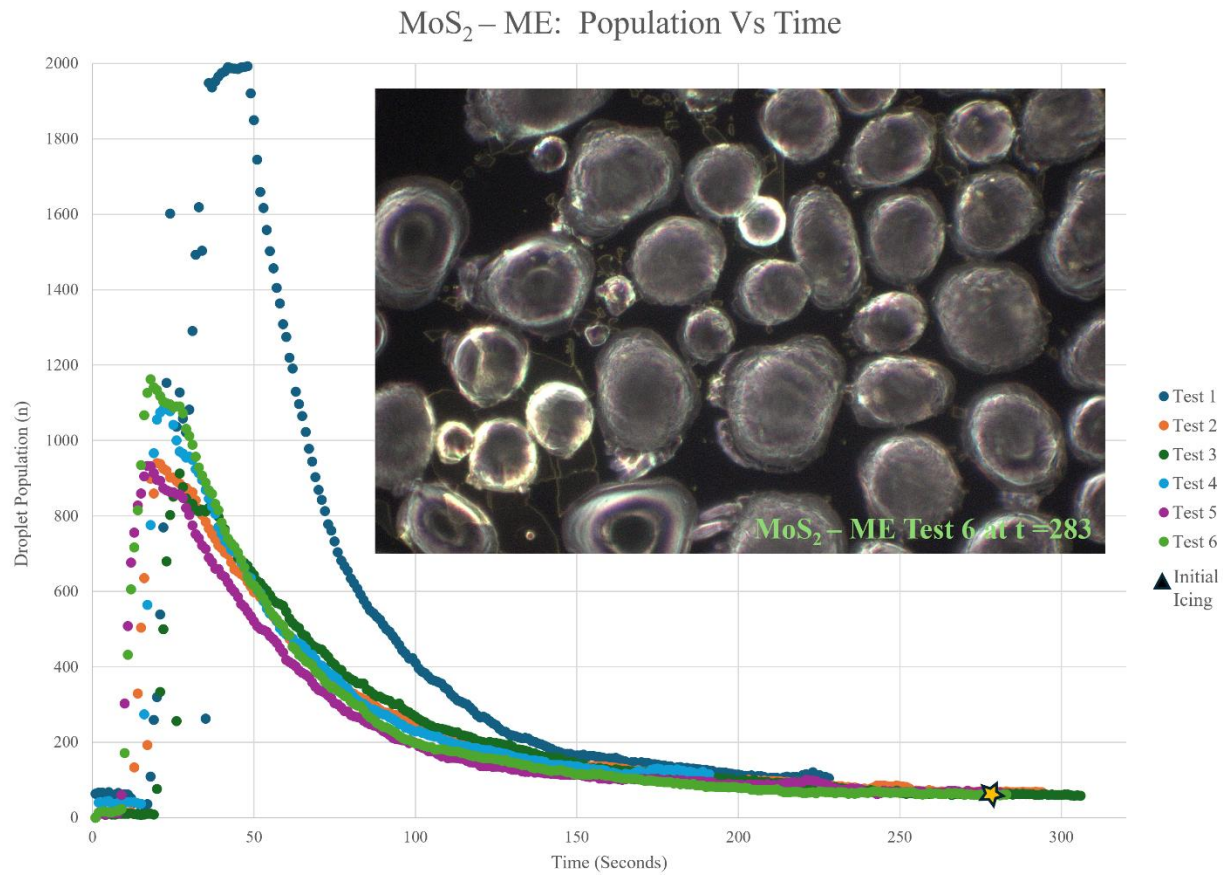


Figure 3.11: MoS₂ - ME Population (*n*) versus time.

3.6.3 Droplet Diameter

All surfaces saw continuous diameter growth until freezing started to occur (Figures 3.12-3.14). Growth rates slowed as populations declined and interdroplet distances increased. Causing a shift away from coal-based growth to direct vapor deposition. The Si control surface exhibited the most irregular diameter trends. This sinusoidal behavior in Figures 3.9, 3.12 and 3.19 shows the frequent re-nucleation observed on the surface. In contrast, the MoS₂ – CVD surface showed a more continuous and uniform increase in droplet diameter across tests, reaching the largest average diameter at initial freezing, $39.92 \pm 5.61 \mu\text{m}$ (Table 3.5). The MoS₂ – ME surface also showed a steady increase in diameter, but over a shorter time range, reaching an average diameter of $33.60 \pm 2.39 \mu\text{m}$ prior to initial freezing (Table 3.5).

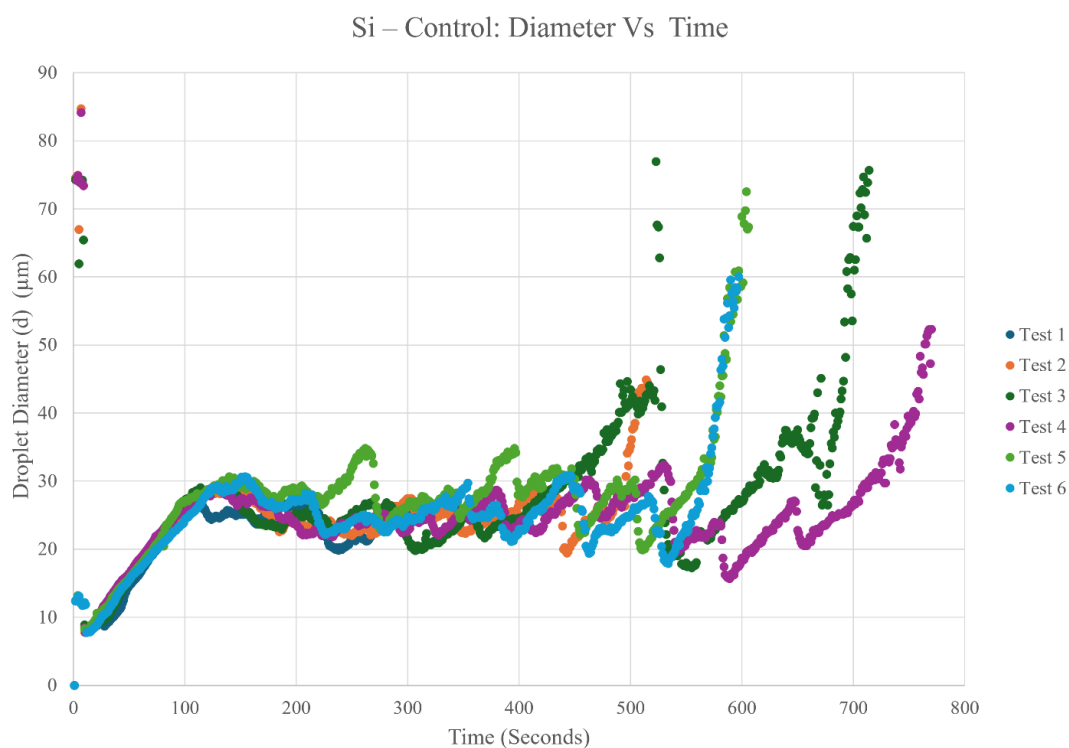


Figure 3.12: Si Control - Diameter (d) versus time

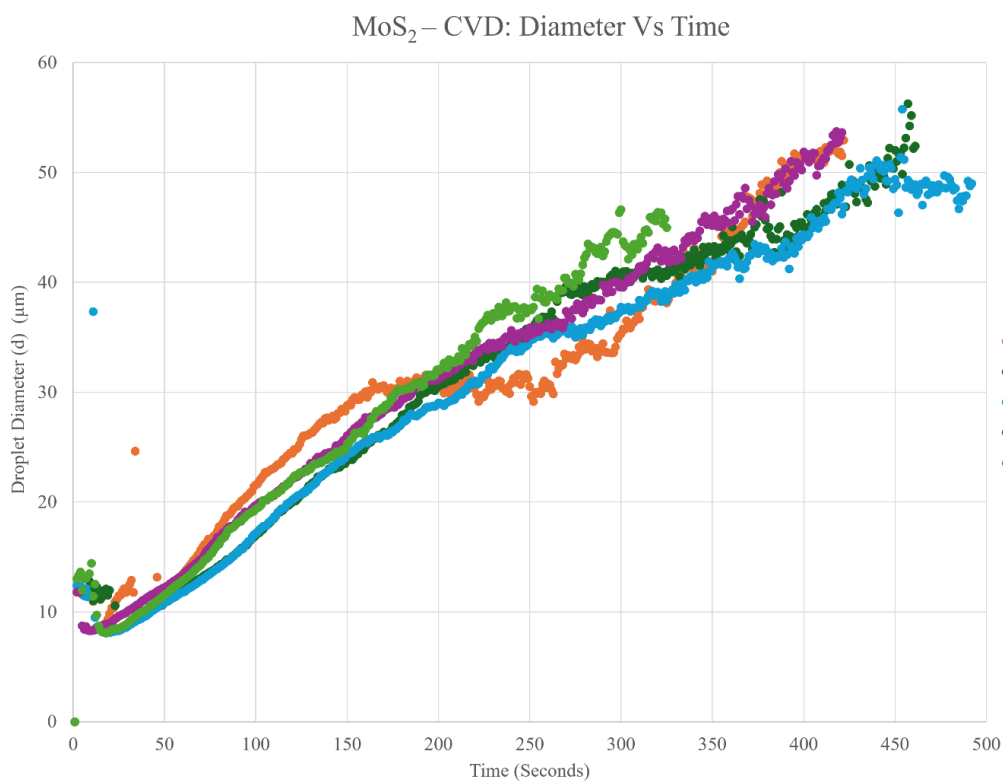


Figure 3.13: MoS₂ – CVD - Diameter (d) versus time

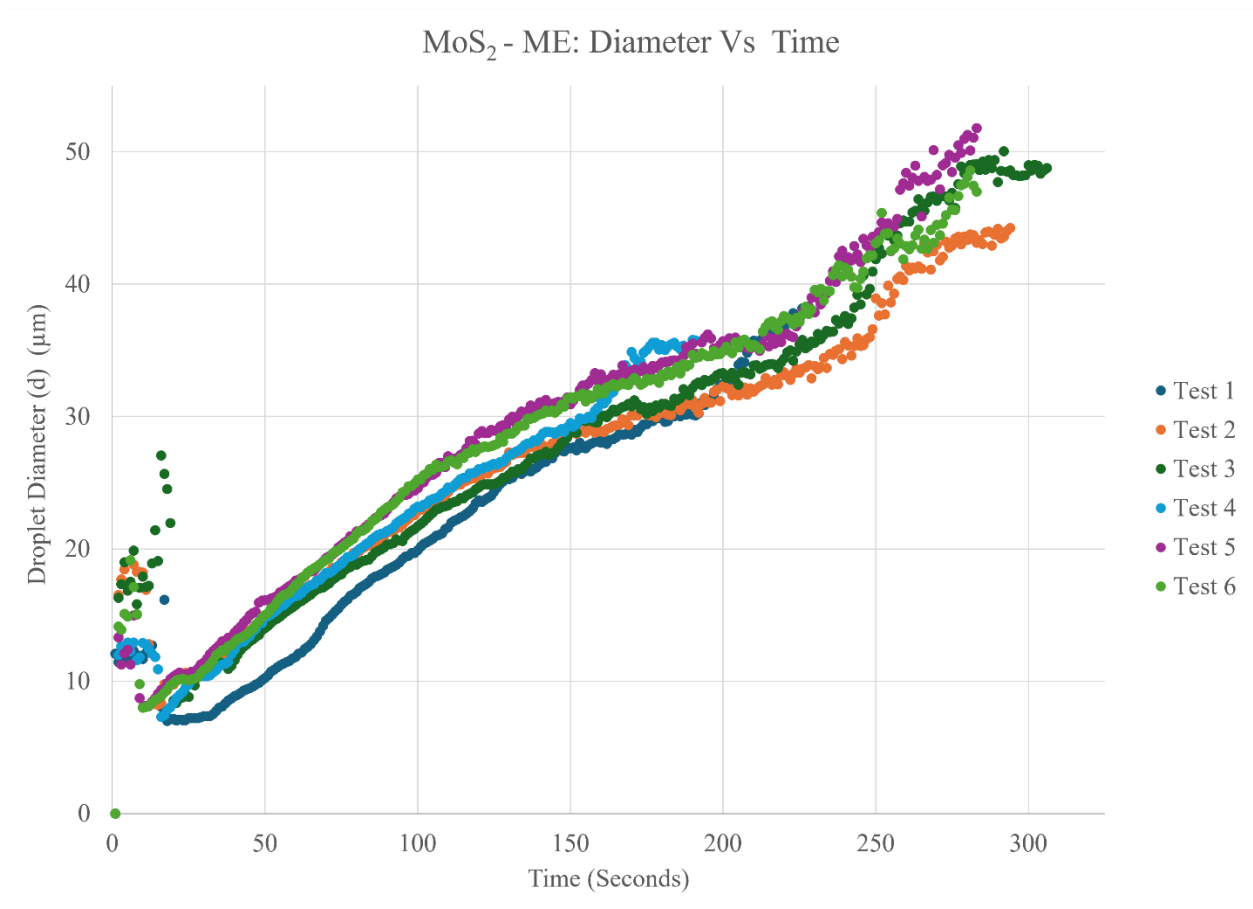


Figure 3.14: MoS₂ - ME - Diameter (*d*) versus time

Table 3.4 : Average Diameter of Droplets at Time of Initial Freezing

Test	Control	MoS ₂ - CVD	MoS ₂ - ME
1	25.12	1	30.67
2	25.95	30.65	34.72
3	31.45	43.42	35.57
4	25.65	42.26	30.00
5	27.74	46.56	35.38
6	18.21	36.74	35.72
Average	25.68	39.92	33.6
Stand Dev	3.95	5.61	2.39

3.6.4 Surface Morphology, Wetting, and Droplet Behavior

On the control surface, an uncoated SiO_x wafer, the coalescence and freezing behavior were typical of what has been observed on other smooth surfaces [1], [50]. The droplet shapes were highly circular. The contact angle increased by 8.31° , from 83.02° to 91.33° , over the course of the experiment, likely due to the natural oxidation of the wafer. Figure 3.11 shows the diameter growth of the control surface. It begins in a normal linear pattern that persists until approximately $t = 100\text{s}$. Then an almost sinusoidal trend dominates until the linear pattern returns late in the process (Figure 3.11). This sinusoidal behavior is the result of the re-nucleation of smaller drops in voided spaces left when large droplets merge (Figure 3.15). The start of linear increase at the end is not indicative of initial freezing, which occurs approximately $\sim 10\text{-}15$ seconds after the second linear increase starts. Not all droplets present at freezing will be present through the phase change. The large droplets freeze, while almost all smaller, re-nucleated droplets sublime into vapor (Figure 3.15). The smaller re-nucleated droplets can be split into two categories: ones that stay and freeze, and ones that sublime. The deciding factor seems to be the diameter, with those less than $15\mu\text{m}$ sublimating and those greater than $15\mu\text{m}$ remaining.

If the re-nucleated droplets are omitted from the average diameter of the control, then the average size of the large droplets formed on this surface increased to a range of $118\text{-}144\mu\text{m}$, depending on the trial. Some of the largest droplets are $200\mu\text{m}$ or greater. This is most likely due to the extremely smooth and polished nature of the surface. The droplets have a high degree of mobility and the opportunity to continue coalescing for a longer time. The lack of surface imperfections, such as scratches or dirt, also delays the heterogeneous formation of ice nuclei [16], [31].

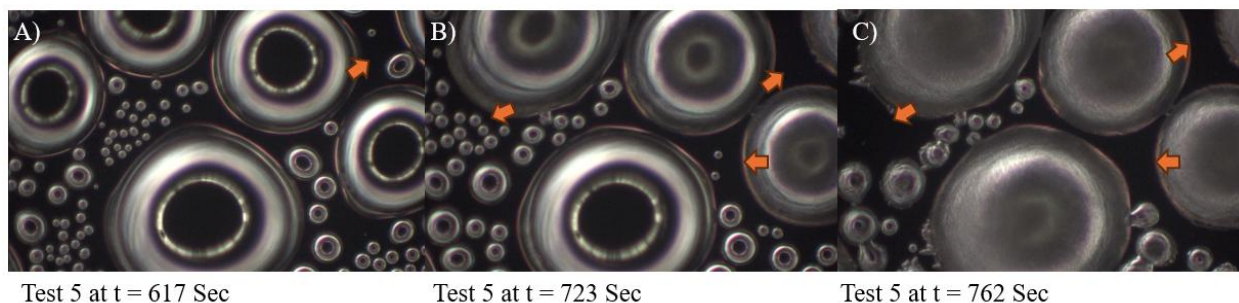


Figure 3.15: Control surface Test 5 at various times. Smaller diameter droplets ($< 15\mu\text{m}$) sublime as the freezing front progresses across the surface.

The CVD sample had a background of blue speckles, as shown in Figure 3.1 A. At high magnification, the hexagonal nature of the MoS_2 flakes is clear (Figure 3.1B). The water droplets remained circular and uniform throughout the coalescence phase. They appear to be highly mobile, frequently coalescing. However, as seen in Figure 3.10, there is very little renucleation on the CVD surface until the droplets reach a diameter greater than 30 microns, around $t = 200$ sec. Then, small variations in the trend lines appear and persist until the end of the experiment.

The tight circularity of the droplets and a contact angle of 92.74° suggest that the MoS_2 -CVD is slightly hydrophobic. The high mobility is observed on the CVD. This may mean that the CVD surface induces a Cassie state. Increased mobility promotes coalescence [16], [31].

Consequently, it is observed that the MoS_2 -CVD displays both the highest droplet population with the largest average diameter compared to both control and ME samples (Tables 3.4 and 3.5).

The freezing regime of the CVD is primarily ice bridging, although it can appear to have cascading freezing events in certain instances. As seen in Figure 3.12, the droplets in Figure 3.12A are seen to be solidified by a cascading event in Figure 3.12B. This is deceptive as these frames are over eight seconds apart. Cascade bridging is characterized by the deci-second nature of the phase change in addition to its distinctive droplet chain formations.

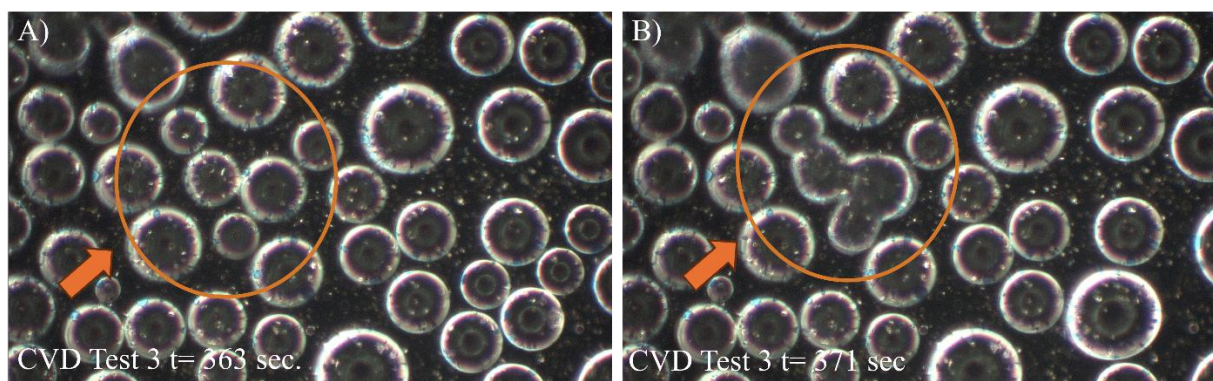


Figure 3.16: A) MoS₂ – CVD Test 3 circled liquid droplets B) MoS₂ – CVD Test 3 eight seconds later. Liquid droplets are now frozen by merging together.

When the water droplets on the CVD cannot move to merge as ice the droplets must resort to ice bridging to continue the freezing front, as seen in the progression in Figure 3.13. The process begins in Figure 3.13B where a long thin dendrite forms to bridge to its far neighbor. Just as this dendrite touches the surface of the neighboring drop in Figure 3.12 C, it is wicked up the dendrite, and subsequently freezes Figure 3.12D.

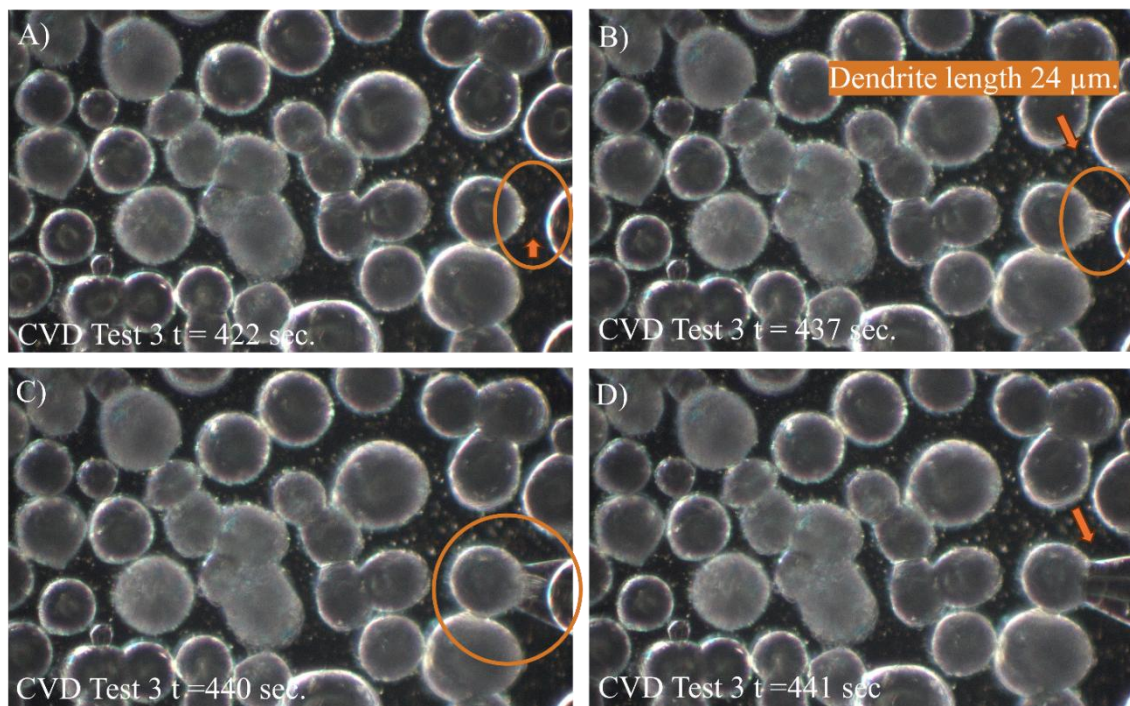


Figure 3.17 A) A 25 micron gap between droplets of interest, B) a dendrite with a length of 24μm has grown, C) the dendrite has touched the liquid droplet and drawn it to the frozen origin drop, and D) the merged new droplet is partially frozen.

The MoS₂ surface produced by mechanical exfoliation presented an archipelago of molybdenum disulfide flakes (Figure 3.2 C). The MoS₂ appears as gold flakes on a black mirror. These flaked sections present a distinctly different behavior than the unadulterated portion of the silicon wafer. Droplets on the ME portions appear to maintain a very high contact angle, as indicated by the roundness of the drops and the bright refraction ring visible at the edges, as seen in Figure 3.14 A. Droplets on this section merged far less often than the surrounding droplets, implying that these droplets are potentially pinned and in the Wenzel state [14], [17]. They also tend to have smaller diameters than the surrounding droplet fields. Since the droplets are pinned, the primary growth mechanism is likely through direct vapor condensation rather than through coalescence.

The droplets on the plain portion of the surface, while mostly uniform in size, are not uniform in shape. A variety of shapes are present, including triangle, rectangle, and diamond (Figure 3.14A). Droplets in this region coalesce frequently. On average, the ME has the smallest droplet diameter of the three samples. They also display a lower contact angle as is visible in the large, clear ‘skirts’ that are visible outside of the refractive halo. This lower contact angle also leads to wide dendrites forming between droplets 3.14B. The primary freezing mechanisms appear to be ice bridging.

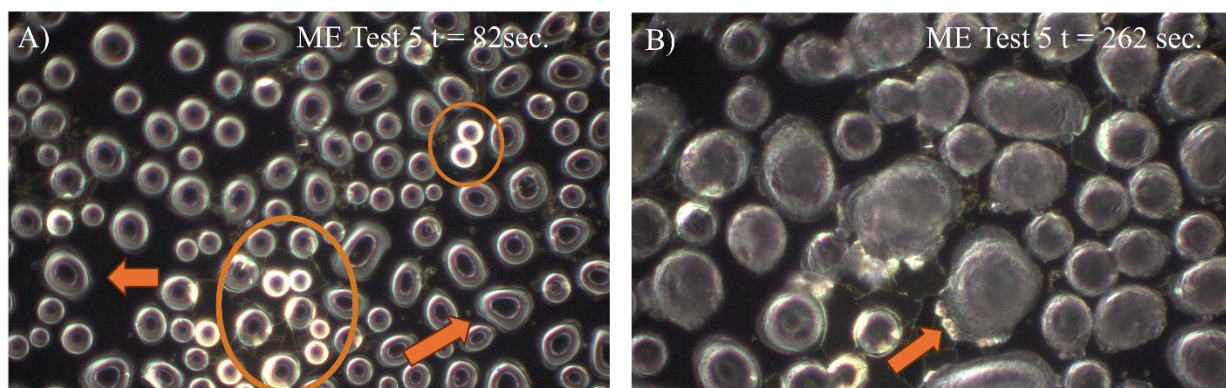


Figure 3.18: A) MoS₂ – ME Test 5 at t = 82 seconds. Orange arrows point droplet irregularities. The right arrow indicates the skirt water showing a lower contact angle. The right drawing attention to the irregular droplet shape. Within the orange circles are droplets formed on the MoS₂ flakes. These are highly circular with high refraction. B) Orange arrow indicates the wide dendrite.

Six different trials per surface were compared, Figure 3.5-3.7. With the exception of Test 1 of the MoS₂ – CVD. This test was omitted due to poor thermal contact that resulted in insufficient heat transfer between the surface and the Peltier cooler. All droplet populations follow a rapid increase to an upper threshold and then transition to a negative exponential trend downwards, which quickly decreases with time, while a positive power law relationship in diameter growth with respect to time is demonstrated in Figures 3.9-3.11. The machine learning model reliably and accurately identified droplets that are 10µm or greater in diameter. Using best-fit functions in Excel, the power law equation was found for each test using. R² values were found to be 0.92 or greater for all surfaces. An average exponent of each relationship was found (Table 3.4)

The control has the longest average freezing time at 621 seconds, followed by the CVD at 425 seconds, while the ME has a rapacious 242-second average freezing time, a little more than 2.5x faster than the control and 1.7x faster than the CVD. At the start of all trials, the surface material is instantly covered with hundreds to thousands of nanoscale droplets. Eventually, these droplets grow and coalesce, and the population stabilizes roughly before initial freezing begins. The data in Table 3.5 were taken at the time of initial freezing for each trial. This was assessed visually and determined when the first liquid droplet in the field changed phase from optical clear to opaque.

Surface coverage is 50% or greater across all surfaces (Table 3.5). The CVD has the largest surface area coverage of 64.4%, roughly an ~8% increase from the control (Table 3.5). Meanwhile, droplets on the ME barely manages to clear the 50% mark in coverage. These differences in surface coverage are not consistent with what one would expect when compared to the total average freezing times.

It would be expected that the surface with the largest average diameter and population and the great abundance of surface coverage would freeze the slowest. Theoretically, it should have the greatest mass and therefore the most latent heat to remove. However, the control is in fact the last to freeze by a significant margin. This is likely due to the skewed average diameter of the control due to the reinoculated droplets on its surface and the lack of nucleation sites on the smooth surface. As the rougher nature of the CVD provides a greater number of nucleation sites for both water vapor and ice nuclei to alight upon.

Table 3.5: Total Freezing Time Analysis (Seconds)

Test	Control	MoS ₂ – CVD	MoS ₂ – ME
1	768	1	221
2	502	445	228
3	502	452	270
4	763	489	182
5	599	422	278
6	589	315	274
Average	621	425	242
Standard Dev.	±109	±167	±35

Table 3.6: Surface Percentage (%) Covered by Water and Ice Droplets

Surface Percentage (%) Covered by Water and Ice Droplets			
Test	Control %	MoS ₂ – CVD %	MoS ₂ – ME %
1	60.17	100.00	55.68
2	49.88	63.97	48.41
3	53.00	65.37	49.03
4	62.53	61.98	51.26
5	56.33	60.39	50.99
6	53.96	70.30	46.41
Average	55.98	64.40	50.30

3.6.5 AI Model Performance

The resulting confidence graphs from the model are shown in Figures 3.15-3.17. The experimental timeline starts at nucleation and ends at complete freezing. As can be seen in Table 3.6, the model achieves 75% confidence early in the process at $t = 37$ sec. , $t = 47$ sec. , and $t = 24$ sec for the control, CVD, and ME, respectively. The model's confidence is reflected by the total number of images annotated at each stage of the process. Due to the large number of hours required to annotate these images, annotation efforts focused on images that show the greatest variety in droplet growth mechanisms (typically in the middle section of the experiments), though considerable efforts have been put toward expanding the annotations for the later stages of freezing front propagation.

Confidence continues to increase, and hovers around 80% for all surfaces, roughly the initial portion of all experiments, and then patterns start to diverge. In Figure 3.15, the control's confidence reaches an average peak of 85% before decreasing and oscillating between 60-85% for the rest of the experiment. This is believed to be due to the large size distribution among the droplets as renucleation starts to take effect. In Figure 3.16, the CVD's confidence level, while consistent between tests, takes on a similar pattern. Confidence increases to the low 80% range around $t = 150$ seconds, takes a dip to the low 60% range, and returns to 70% or greater for the rest of the process. Lastly, the ME produces a graph with better agreement. It is the fastest to arrive at a confidence level of 75% or greater at $t = 24$ seconds, it proceeds to the mid 80% range and stays there until freezing begins. It is noted that both ME Test 1 and 4 display significant dip at $t = 225$ s and 175s that thus far seem to have no physical correlation to either numerical or visual data. However, heat mapping of the neural network during these periods may reveal more information.

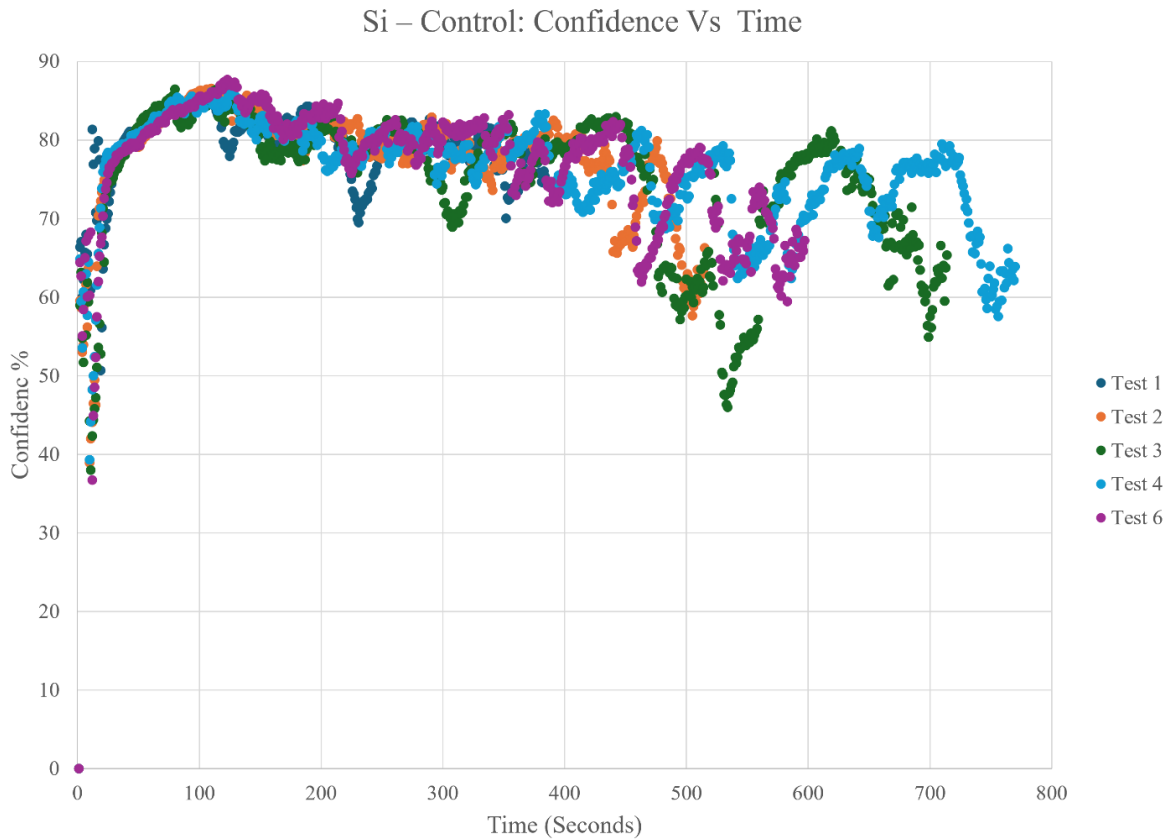


Figure 3.19: Si – Control Vision Model Confidence % Vs. Time (Seconds)

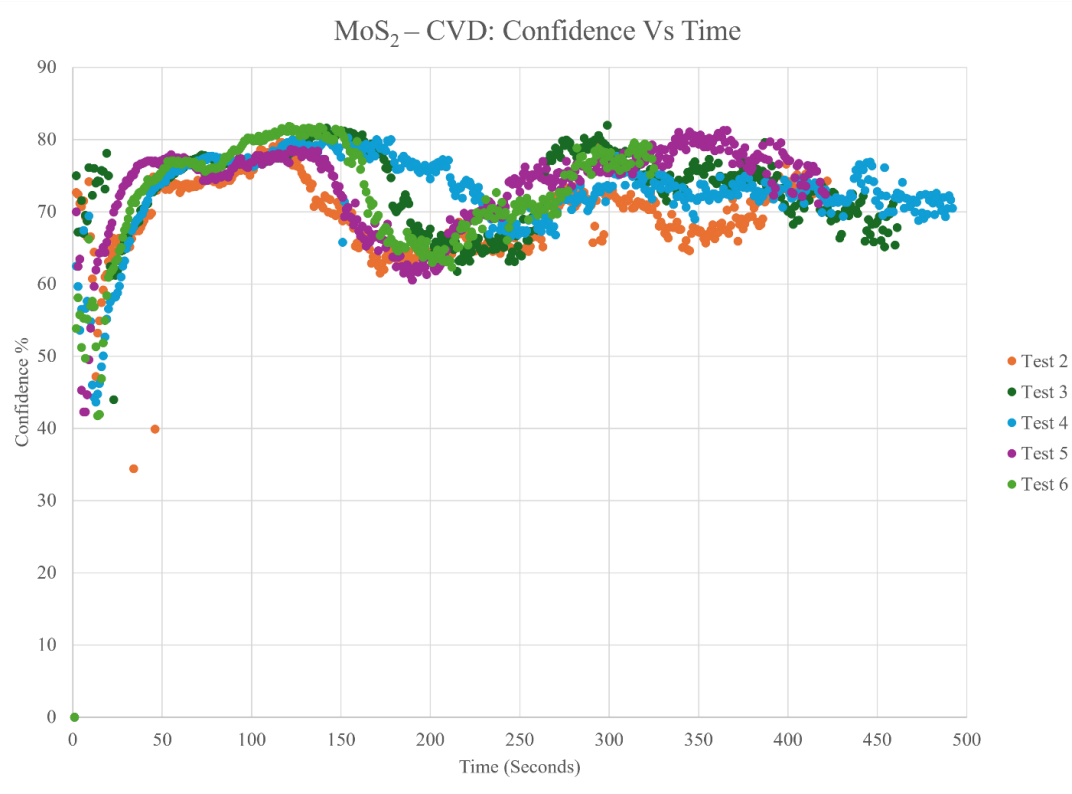


Figure 3.20: MoS₂ – CVD Vision Model Confidence % versus time (Seconds)

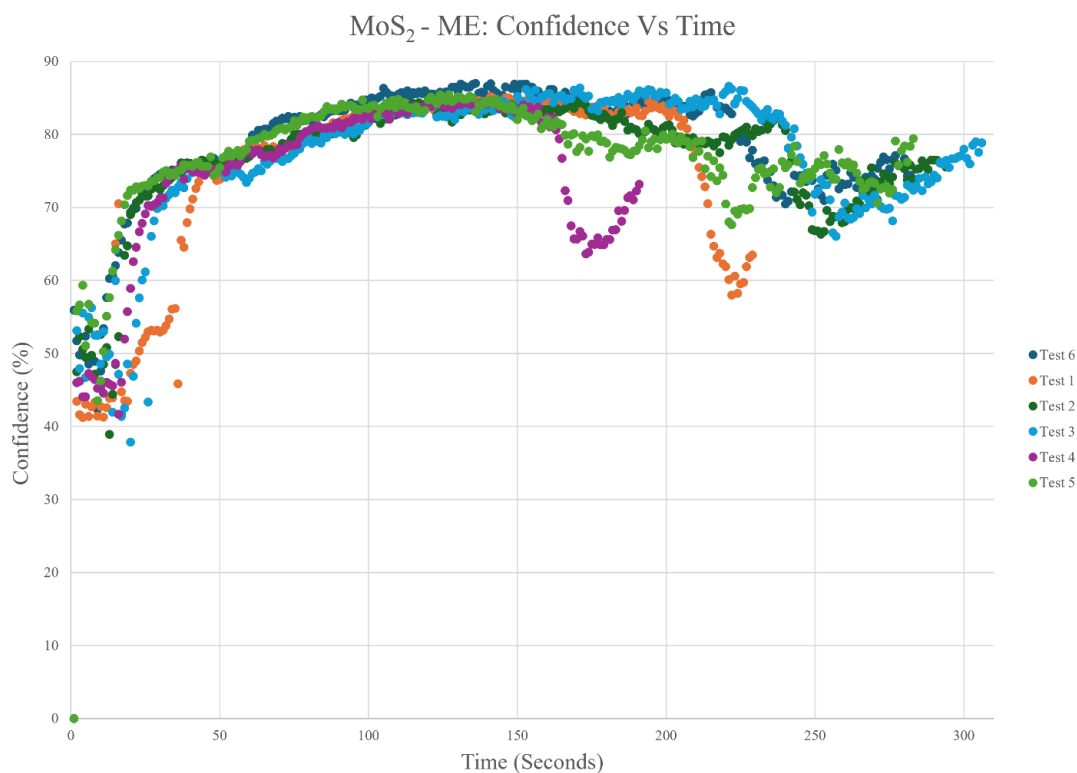


Figure 3.21: MoS₂ – ME Vision Model Confidence % versus time (Seconds)

Table 3.7: Diameters and times reached when the computer vision model achieved a value of 75% confidence or greater.

Surface Type	Control		CVD		ME	
Test	Time (Sec.)	Droplet Dia (μm)	Time (Sec.)	Droplet Dia (μm)	Time (Sec.)	Droplet Dia (μm)
1	45	9.50	1	1.00	28	8.69
2	35	12.08	89	19.59	23	10.76
3	38	11.58	55	11.40	28	9.75
4	34	11.09	54	11.29	20	9.75
5	35	13.01	32	10.40	19	9.73
6	34	12.14	48	11.39	24	9.97
Average	37	11.57	47	10.85	24	9.78

3.7 Discussion

All droplet fields, while highly consistent on the same surface, are visually distinct between samples. The control had highly circular droplets, which eventually developed into an extremely large size distribution by the end of its liquid phase. The control's largest droplets ranged in diameter from 150-225 μm , and the re-nucleated population varied from 5-35 μm (Figure 3.11). This variation in size was highly influenced by the surface's tendency to be coalescence driven, leaving large enough voids for re-nucleated populations to appear.

The CVD had both highly consistent circular geometry and a small range in the size distribution of droplets. The observed re-nucleated rate was low on this surface compared to the control or ME, even though there were many more merging events. The ME was singular in its behavior; the droplets had low contact angles and visually they displayed as clear skirts outside of the refracted light ring (Figure 3.14A). They merged often at the beginning of the test and slowed in their merging, on average, between $t = 125$ sec. and $t = 175$ sec. (Figure 3.7). They also displayed more irregular geometry in their shape.

Droplets on the smooth portions of the ME surface formed diamond, triangular, and even square droplets. This behavior was also observed on a structured nano pillared surface in Bohm et al. 2018 [41]. It is hypothesized that the greater number of nano surface features, fragments of

MoS₂, from the application process held the edges of the droplet in place while merging continued to occur, leading to these remarkable shapes. In addition, on the ME's large visible flakes of MoS₂, the droplets displayed a different and consistent shape (Figure 3.14A). Highly circular and but immobile, these droplets grew significantly slower than their neighbors on the smooth parts. It is believed these isolated droplets primary growth method was through direct vapor condensation.

Droplet pinning and coalescence play a significant role in governing freezing behavior. In the cases of the MoS₂ – CVD and ME, pinning is seen to influence the additional aspects of growth regimes, surface coverage, and upper size limit. The fact that the CVD has largest average droplet diameter and great surface area coverage of water is telling of the impacts of droplet mobility impact on growth, followed in both categories by the control. If a droplet is mobile, it is to be expected that its population will grow larger in diameter at a faster rate than a surface that is experiencing pinning.

Conversely, a pinned water droplet population's average droplet size will grow less dramatically, as it must rely more on direct vapor deposition for growth, and may have less surface area coverage, as is the case with the ME. This increased solid-liquid contact area and pinning both lowered the energy barrier for heterogeneous nucleation and improved heat transfer from the droplet to the substrate [20], [21]. Allowing a pinned population of droplets to freeze faster than on a more mobile substrate.

However, a lower surface energy is not the only reason the ME is the most rapacious freezing surface in this study. Nano surface structures affect how a droplets rests on that surface [e.g. in either a Wenzel or Cassie state (Figure 1.3)]. It is suspected of the variation in freezing times between surfaces is that the CVD droplets are in a Cassie state and the ME droplets in a Wenzel state.

If this is true, it would have a number of physical implications. If the CVD induces a Cassie-Baxter state, this increased freedom of movement would allow droplets to coalesce more frequently and reach a larger diameter, in this instance ~40 μm diameter (Table 3.3). However, because the droplets is resting on top of the gaps created from the even dispersion of MoS₂

flakes, it has less capacity to remove latent heat due to both a reduced liquid-solid contact area and the air gaps beneath it acting as insulation. Thus, leading the CVD to freeze slower than the ME.

The reduced mobility and lower contact angle of the ME may indicate a Wenzel state. Droplets on the ME surface fill in the gaps in the existing nano texture. This infilling creates a continuous liquid-solid contact area greater than that of a similarly sized droplet in a Cassie state. Therefore, the droplets on the ME surface are able to shed latent heat far more effectively than a similar droplet in a Cassie state [24], [27].

The modification of the substrate resulted in other measurable changes in droplet growth dynamics exhibited as a shift in the power law exponent governing droplet radius evolution and population, $R \sim t^\alpha$ [26], [27]. For all surfaces, droplet growth follows a scaling consistent with coalescence-dominated growth, where population grows $n \propto t^{-\alpha}$ and droplet diameter grows $d \propto t^\alpha$ [23], [26]. It can be inferred from the high alpha value of the CVD, $d \propto t^{0.73}$, that it does indeed have the greatest mobility of all the surfaces (Table 3.2), greater than even the smooth and polished control surface, $d \propto t^{0.69}$. The ME has a modest exponent value of $d \propto t^{0.63}$, emphasizing the likelihood of its reduced mobility. The change in exponents is characteristic of systems where enhanced droplet pinning and reduced mobility prevent coalescence [23], [27].

The exponents for diameter from greatest to least are CVD, control, and ME. However, this pattern is not inverted in the population's exponent order as would be expected and is ordered ME, CVD, and control. The ME has the largest alpha value governing population, $p \propto t^{-1.3}$, when compared to the CVD and control, $p \propto t^{-1.0}$ and $p \propto t^{-0.91}$. These discrepancies between surfaces are likely a reflection of droplet mobility, conflated with droplet diameter and the opportunity for ice nucleation.

The ME surface experiences the greatest pinning effect due to irregular surface texture and therefore has the smallest drops. This unevenness of the MoS₂ flakes added to the silicon substrate increased heterogeneous nucleation sites and promoted ice growth and faster freezing on the ME, in addition to a lower threshold energy, leading to a faster population decline in this sample [2] [41]. Viewed through the lense of surface roughness, the corresponding descending order of population exponents from roughest to smoothest correlates with other literature [7], [20], [21], [41].

3.8 Conclusions

This chapter examined how MoS₂ flake application methods influenced condensation growth, droplet mobility, and freezing rates on silicon substrates. The control, MoS₂ - CVD, and MoS₂ - ME surfaces each produced distinct condensation patterns and freezing behaviors. The MoS₂ - CVD surface had the highest average contact angle, greatest average droplet population, largest average droplet diameter at initial freezing, and the most surface coverage prior to freezing. These results suggest that the more uniform CVD coating promoted droplet mobility. Allowing droplets to grow through repeated coalescence before freezing.

In contrast, the MoS₂ - ME surface produced the smallest average droplet population and the fastest average freezing time (Tabel 3.5 and 3.7). The irregular distribution of mechanically exfoliated flakes promoted droplet pinning and more rapid ice formation. This is most likely due to an increased solid-liquid contact area induced by a Wenzel state and the increased number of heterogeneous nucleation sites.

The control exhibited behavior unlike the altered sub straights. Observationally it demonstrated the highest droplet mobility. Creating adequate distances between droplets to foster repeated renucleation of droplets. With higher droplet mobility, the smooth surface allowed the largest droplets to form. However, the larger mass and fewer nucleation sites lead the slowest time to complete freezing.

Overall, the results indicate that both MoS₂ application methods can measurably alter condensation and frost dynamics. The major conclusions from this chapter are:

- MoS₂-CVD promoted the highest droplet population, largest average droplet diameter, and greatest surface coverage.
- MoS₂-ME froze the fastest, suggesting a greater surface roughness and droplet pinning, accelerating nucleation and frost propagation.
- The control surface allowed the most frequent coalescence and exhibited re nucleation due to its smoothness. This lead to the largest droplets. The uniform smoothness also lacked heterogeneous nucleation sites for ice. These factors most likely led to it having the longest average freezing time.

- The neural-network image analysis was able to capture the major trends in droplet population, droplet diameter, and freezing progression, although bright MoS₂ flakes and surface defects reduced model confidence.

The machine learning model helped establish a direct link between changes in power law relationships and accelerated icing on the different MoS₂-coated surfaces. Results of the altered sub-straight samples indicate that increased surface topography enhances droplet pinning, thereby decreasing freezing time. These findings support the use of MoS₂-coated surfaces as a platform for further study of frost-control surface design.

Chapter 4 : Conclusions and Future Work

⁵This work utilizes a YOLO-based artificial vision model to assess droplet population, average droplet diameter, surface coverage, and phase change. In Chapter 2, condensation and freezing behavior on smooth and laser-patterned aluminum surfaces were investigated. The results showed that adding microtexture to a surface measurably changed its condensation and ice dynamics. Added texture increased droplet pinning and reduced mobility. This shifted the droplet growth behavior away from coalescence and toward direct vapor condensation. On the smooth aluminum control surface, droplet mobility was greater. Thus, droplets grew more readily through coalescence, producing larger droplets and slower freezing times. This change was reflected in the power law trends for droplet population and diameter, as indicated by a 3× increased fretting rate of the microtextured surface compared to the control.

Chapter 3 combined both the experimental approach and AI evaluation of Chapter 2 for silicon substrates coated with molybdenum disulfide. Two application methods of MoS₂ were utilized to apply flakes to the substrate: chemical vapor deposition (CVD) and mechanical exfoliation (ME). The control, MoS₂ - CVD, and MoS₂ - ME surfaces each exhibited distinct behaviors, including wetting, freezing times, and population and diameter growth trends.

^{5 5} Portions of this chapter were published in: Turner, Jane C., Aryan Singh Dalal, Hande Küçük McGinty, Melanie M. Derby, and Amy R. Betz. "Examining condensation and freezing behavior on a laser-patterned metallic surface using an AI neural network model." *Frontiers in Thermal Engineering* 6 (2026): 1808591.

The MoS₂ - CVD surface produced the droplet population, surface coverage, and average droplet diameter at initial freezing. This suggests that the significantly smaller and more uniform flake coating may have induced a Cassie state, promoting droplet mobility and increasing coalescence. In contrast, the MoS₂-ME, with its greater surface roughness surface produced the smallest average droplet population and the fastest freezing time. It is likely that increased surface roughness induced a Wenzel state, thereby increasing both pinning. Also providing of a far greater number of heterogeneous nucleation sites.

Together, these studies show that condensation frosting is strongly governed by the interaction between surface texture, wetting state, droplet mobility, and heat transfer. Both the metallic and MoS₂-coated surface sets showed that promoting droplet mobility allowed more frequent coalescence and greater droplet growth before freezing. Surfaces that increased pinning tended to accelerate ice formation by reducing average droplet size, increasing solid–liquid contact area, providing additional nucleation sites, and lowering the energy barrier for heterogeneous nucleation.

The use of a neural-network vision model was central to this work. The model enabled full-field evaluation of thousands of droplets throughout time frame of the experiment. This would be impossible to do manually. Statistical robustness enables linking observable changes in droplet behavior to measurable power law trends and freezing outcomes. These results emphasize that frost behavior cannot be predicted solely from a few variables. Instead, a holistic view including wettability, straight material, surface defects, and added geometry must be considered in order to influence freezing and engineer an ice-phobic surface.

Two paths for future work are apparent moving forward. The first is testing of other altered surfaces and substrates; this includes physically altering the geometry of the surface or adding a surfactant to alter wettability. Secondly is a focus on increasing the model's annotated data set. Additional annotations of all portions of the nucleation-coalescence-freezing timelines would significantly improve the accuracy of current model features. Additionally, having a feature that would track and identify the mechanism of freezing front, such as an ice bridge, stochastic or cascade event would deeply help the understanding of frost dynamics

Chapter 5 : References

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