Poster P-158 has been designated as a Distinguished Poster at Display Week 2025. The full-length version of this paper appears in a Special Section of the *Journal of the Society for Information Display (JSID)* devoted to Display Week 2025 Distinguished Papers. This Special Section will be freely accessible until December 31, 2025 via:

https://sid.onlinelibrary.wiley.com/doi/full/10.1002/jsid.2065

Authors that wish to refer to this work are advised to cite the full-length version by referring to its DOI:

https://doi.org/10.1002/jsid.2065

Early Detection of Crack Vulnerability in Foldable Displays Through Critical-Angle Curvature Analysis

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Abstract

Foldable displays have become increasingly popular due to their portability and the provision of larger screens when unfolded. However, the use of flexible materials makes them more susceptible to mechanical failures, particularly crack formation in the hinge area where stress concentration is highest during folding operations. This study presents a novel approach to predict crack formation in foldable displays by measuring the curvature of the hinge area at a specific critical angle—where the mechanical stress peaks—and analyzing this data using Principal Component Analysis (PCA). The curvature measurements were initially reduced using PCA, retaining two principal components that captured around 60% of the dataset's variance. While this facilitated visualization, it was insufficient for clear classification between defective and non-defective samples due to overlapping data points and information loss. To enhance predictive accuracy, we introduced an uncertainty quantification method based on a -nearest neighbors approach with distance-weighted contributions. This method calculates an uncertainty score for each sample, reflecting the confidence in classifying it as susceptible or resistant to cracking. By integrating the uncertainty analysis into an artificial intelligence (AI) model, we assigned a numerical score ranging from +1 (clearly non-defective) to -1 (high risk of cracking) to each sample. Applying this model to a larger dataset of 200 samples, we successfully quantified the risk of crack occurrence—a task previously unfeasible with conventional methods. The model demonstrated strong discriminative power, effectively distinguishing between at-risk and safe samples. This integrated methodology combining precise curvature measurement, uncertainty analysis, and AI modeling provides a robust framework for early detection and prediction of crack formation in foldable displays. The approach enhances product reliability and contributes valuable insights into material behavior under stress, supporting improved quality control measures in manufacturing. Future work will focus on expanding the dataset and incorporating additional features to further refine the model's predictive capabilities.

Author Keywords
Foldable Display, Crack

1. Introduction

Foldable displays represent a transformative advancement in consumer electronics, seamlessly merging portability with expanded screen functionality to enhance user experience. [1] These devices have garnered significant consumer interest and commercial success due to their ability to enhance user experience by seamlessly transitioning between compact and expansive display modes. The continuous demand for more versatile and user-friendly devices underscores the need for ongoing advancements in foldable display technology.

However, the incorporation of flexible materials and components, which is fundamental to the functionality of foldable displays, introduces new challenges not present in traditional rigid displays. One of the most critical issues is the increased susceptibility to mechanical failures, such as crack formation. [2] This vulnerability is especially acute in the hinge area—the central folding mechanism of the device—where mechanical stress is most concentrated during operation. Even minor manufacturing tolerances or defects can become significant over time, leading to the initiation and propagation of cracks after prolonged use (Fig. 1). Such defects not only compromise the structural integrity and longevity of the device but also diminish user satisfaction and trust in the technology.

Addressing these challenges is essential for the sustained growth and adoption of foldable displays. Traditional methods of quality control and defect detection may not be sufficient due to the complex mechanical behaviors associated with flexible materials. Therefore, innovative approaches are required to predict and mitigate potential failures before they manifest in the end product.

In this paper, we propose a novel method leveraging artificial intelligence to analyze and preemptively identify samples that are vulnerable to future crack formation. By utilizing advanced AI algorithms and machine learning techniques, we aim to detect subtle indicators of potential mechanical failure that may not be apparent through conventional inspection methods. This proactive approach allows for the early identification of at-risk components, enabling manufacturers to address issues before they affect product performance. Our research contributes to the enhancement of reliability and durability in foldable display technology, paving the way for its continued evolution and consumer acceptance.

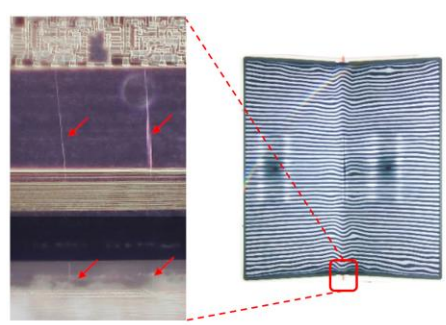

Fig. 1 This demonstrates the progression of crack formation in the hinge area, attributable to cumulative stress during repeated folding cycles. This region is particularly susceptible to mechanical failure, and prolonged cycles of opening and closing exacerbate stress, leading to crack initiation and propagation as shown in the left image.

ISSN 0097-996X/25/5603-2048-$1.00 © 2025

2. Hinge Curvature analysis

Building upon the extensive experience of our engineering team, we hypothesized that by measuring the curvature of the hinge area when the internal panel component of a foldable display is unfolded to a specific angle−where the stress is at its maximum−we could indirectly calculate the stress and predict potential future crack formation based on this information. This specific angle is critical because it represents the point at which the mechanical strain on the device is most pronounced, making it an ideal condition for assessing structural integrity.

Initially, we attempted to distinguish differences in stress and potential crack formation through visual inspection. However, this method proved insufficient; while general tendencies could be observed, accurately quantifying these observations was challenging. The subjective nature of visual assessments made it impractical for application in mass production environments where consistency and precision are paramount. Moreover, the inherent properties of flexible devices introduced additional complications. After unfolding to the angle of maximum stress, the curvature of the device does not remain constant but changes over the span of a few seconds due to material relaxation and viscoelastic effects, as illustrated in Fig. 2. This transient behavior further hinders the reliability of visual judgment and underscores the need for a more precise measurement approach.

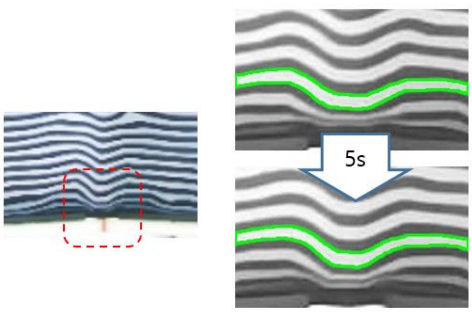

Fig. 2 This illustrates the importance of initial measurement when assessing the curvature of a foldable display's surface at a specific angle (less vjthan 180 degrees). Since the device utilizes flexible display elements, its surface curvature can change over time. Therefore, early measurements are crucial to accurately capture the device's initial bending characteristics.

- Curvature PCA analysis

Through rigorous stress testing involving repeated cycles of opening and closing, we collected data on both defective (cracked) and non-defective samples, specifically measuring the initial curvature at the critical vulnerable angle. These curvature profiles were subjected to Principal Component Analysis (PCA), reducing the multidimensional data to two principal components that account for approximately 60% of the total variance (Fig. 3). [3][4] In the resulting two-dimensional PCA plot, samples that developed cracks are represented by red dots, while non-defective samples are depicted as blue dots.

Despite the limited number of samples−owing to constraints inherent in reliability evaluations−the scatter plot reveals a general tendency and suggests a potential boundary between defective and non-defective samples. However, a clear and definitive separation is not evident. This lack of distinct demarcation may be attributed to several factors. First, the use of only two principal components means that not all the information contained in the original data is captured, possibly omitting critical features necessary for accurate classification. The retained 60% variance might be insufficient to encapsulate the complexity of the curvature profiles related to crack formation. Second, relying solely on the initial curvature measurements at the vulnerable angle may not provide enough discriminatory power to distinguish between samples that will develop cracks and those that will not.

To further investigate these limitations and enhance the predictive capability of our analysis, it is necessary to incorporate additional uncertainty analysis. By quantifying the uncertainty associated with each sample's position in the PCA space, we can better understand the overlap between defective and non-defective samples. This approach can help identify whether the ambiguity arises from intrinsic data variability, measurement errors, or inadequate feature representation. Incorporating uncertainty measures may also facilitate the development of more robust classification boundaries and improve the overall reliability of crack prediction in foldable displays.

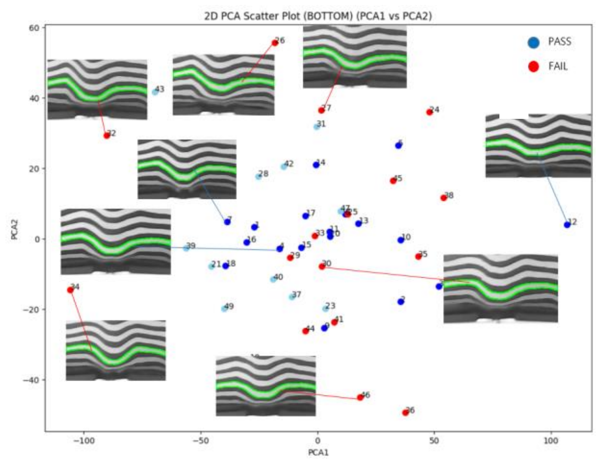

Fig. 3 This figure illustrates the two-dimensional distribution obtained by applying Principal Component Analysis (PCA) to the bending shapes of the hinge area in foldable devices measured at the critical angle. Blue dots represent normal samples, while red dots indicate samples where crack defects have occurred. This visualization highlights the differences in bending characteristics between normal and defective samples.

3. Uncertainty analysis and modeling

In this study, we aim to analyze and quantify the uncertainty inherent in the curvature measurements and reliability evaluation results obtained from our experiments. By addressing this uncertainty, we seek to more precisely identify and distinguish between samples that are prone to crack formation and those that are considered safe.

To achieve this, we developed a mathematical model to calculate an uncertainty score for each data point based on its proximity to neighboring samples and their respective class labels (defective or non-defective). [5][6] The uncertainty score for a given data point is defined using the -nearest neighbors approach as follows:

$$U(x_i) = \frac{\sum_{x_j \in \mathcal{N}_k(x_i),\, \mathrm{Class}(x_j) \neq \mathrm{Class}(x_i)} w(d_{ij})}{\sum_{x_j \in \mathcal{N}_k(x_i)} w(d_{ij})}$$

where:

x_i is the data point for which we are calculating the uncertainty.

$\mathrm{Class}(x_i)$ denotes the class label of x_i (either defective or non-defective).

$N_k(x_i)$ represents the set of k-nearest neighbors of x_i with distances d_{ij} for each neighbor x_j in $N_k(x_i)$

$\mathrm{w}(d_{ij}) = e^{-d_{ij}}$ is a weighting function based on distance, assigning higher weights to closer neighbors.

The numerator of the equation sums the weighted contributions of neighboring samples whose class labels differ from that of , while the denominator sums the weighted contributions of all neighboring samples. An uncertainty score close to 1 indicates high uncertainty (as most nearby samples belong to a different class), whereas a score close to 0 indicates low uncertainty (as most nearby samples share the same class). (Fig.4)

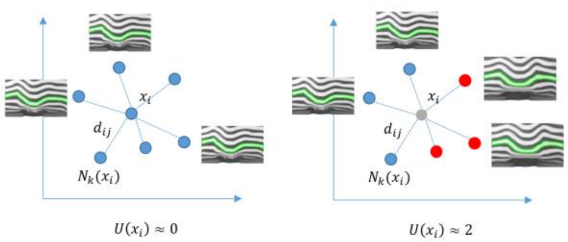

Fig. 4 This illustrates the concept of measuring the uncertainty of information obtained from experiments and measurements, which is crucial during the research stage when the number of samples is limited. In the PCA plot, data points surrounded by homogeneous information (i.e., similar nearby data points) are considered to have higher confidence. Conversely, data points with a heterogeneous neighborhood are judged to be more uncertain. This visualization emphasizes how the proximity of similar data in PCA space can influence the assessment of data reliability under conditions of sample scarcity.

By applying this method, we can effectively mitigate the uncertainty arising from experimental measurements and enhance the precision of our analysis. This allows us to more accurately quantify and distinguish between samples that are susceptible to crack formation and those that are not.

The results of this uncertainty analysis are depicted in Fig. 5. The curvature shapes measured at the critical vulnerable angle reveal distinct patterns. Samples that are safe exhibit a sharp V-shaped curvature, indicating a more acute bend. In contrast, samples prone to cracks display a slightly flattened U-shaped curvature. This difference suggests that deviations from the original design specifications–possibly due to minor production errors–can lead to variations in stress distribution during folding operations.

The presence of these variations implies that certain samples may experience abrupt changes in mechanical stress, increasing their susceptibility to crack formation over time. By employing our uncertainty analysis method in conjunction with AI techniques, we can detect these subtle differences in curvature profiles. This enables us to preemptively identify and classify at-risk samples during the production process.

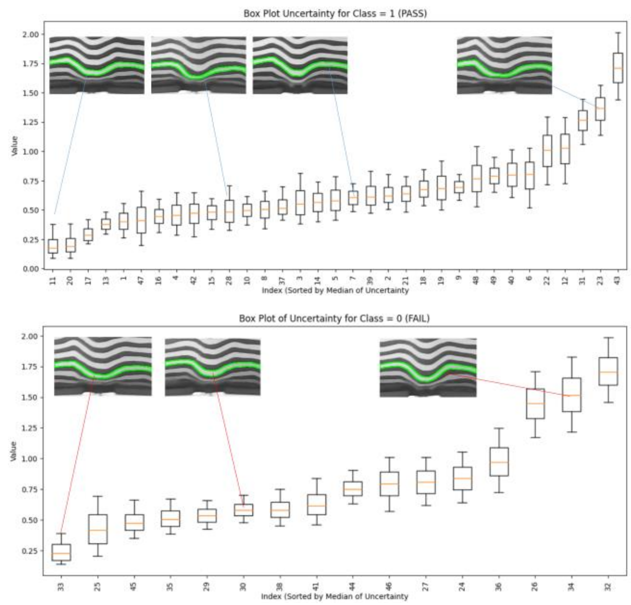

Fig. 5 This presents the results of measuring the uncertainty for each sample. Since the uncertainty values vary depending on the number of neighboring samples referenced, we have depicted their distribution. The upper left image clearly demonstrates a strong tendency toward being highly resistant to cracks. In contrast, although the sample in the upper right image passed the reliability evaluation, it exhibited a vulnerable form. Additionally, the lower left image shows a tendency toward being highly susceptible to crack occurrence.

Building upon the uncertainty measurements obtained from our relatively small initial sample set, we developed an AI model designed to assign a numerical score to each sample. This score ranges from +1 to -1, where +1 signifies a clearly non-defective (good) product, and -1 indicates a product that is clearly at risk for future crack formation. We applied this model to a larger dataset consisting of 200 samples to evaluate its effectiveness. The results of this application are illustrated in Fig. 7.

The implementation of this AI-driven scoring system enabled us to quantify the risk of crack formation—a task that was previously unfeasible with traditional methods. By translating complex curvature and stress data into a simple numerical score, we provided a clear and quantifiable measure of each sample's susceptibility to cracking. This quantification not only facilitates easier interpretation and decision-making but also enhances the precision of reliability assessments.

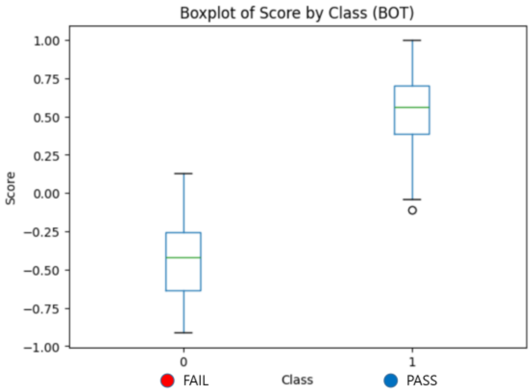

Fig. 7 This presents the results of measuring a large volume of mass production data after modeling based on the previously assessed judgment uncertainty. The data have been recalculated into a score value, where a score of +1 indicates a good product with strong confidence, and values approaching -1 signify a defective product with strong confidence. Around the score of 0—an interval where judgment is difficult—there is an overlap between good and defective products. However, to minimize leakage, the decision boundary can be strategically restructured. This allows for the adjustment of classification thresholds to better separate good products from defective ones, enhancing the reliability of the assessment.

4. Conclusion

This study addresses the pressing challenge of enhancing reliability in foldable displays by introducing a robust predictive framework for crack formation. Recognizing the limitations of visual inspection—especially given the transient nature of curvature in flexible materials—we developed a specialized measurement system to capture the curvature profile at the precise moment the display is unfolded to its critical vulnerable angle. This approach allowed us to obtain accurate representations of the device's mechanical state under maximum stress conditions.

By applying Principal Component Analysis (PCA) to the collected curvature data, we reduced the dimensionality of the dataset, capturing approximately 60% of the total variance with the first two principal components. While this reduction facilitated visualization and initial analysis, it also highlighted the challenge of information loss, as the two-dimensional PCA plot did not provide a clear boundary between defective and non-defective samples due to overlapping data points.

To address this limitation, we introduced an uncertainty quantification method based on a -nearest neighbors approach with distance-weighted contributions. This method allowed us to calculate an uncertainty score for each sample, effectively capturing the degree of confidence in classifying it as either susceptible or resistant to crack formation. By incorporating this uncertainty analysis into our AI modeling, we enhanced the model's ability to discriminate between at-risk and safe samples.

Implementing the AI model, we assigned a numerical score ranging from +1 to -1 to each sample, where +1 indicates a clearly non-defective product and -1 signifies a product at high risk for future crack formation. Applying this model to a larger dataset of 200 samples, we successfully quantified the risk of crack occurrence—a task previously unfeasible with conventional methods. The results demonstrated strong discriminative power, confirming the model's utility in handling large volumes of production data and enhancing the precision of reliability assessments.

In conclusion, our integrated approach combining precise curvature measurement, uncertainty analysis, and AI modeling provides a robust framework for predicting crack formation in foldable displays. This methodology not only improves the reliability and longevity of the devices but also contributes valuable insights into the material behaviors under stress. By enabling early detection of potential mechanical failures, manufacturers can implement proactive quality control measures, ultimately enhancing consumer trust and acceptance of foldable display technology.

Future work may focus on expanding the dataset to include a broader range of samples and stress conditions, which would further validate and refine the predictive capabilities of the model. Additionally, exploring more advanced machine learning techniques and incorporating additional features beyond curvature—such as material properties and environmental factors—could enhance predictive accuracy. Through continued research and development, we aim to contribute to the advancement of durable and reliable foldable electronic devices, supporting their sustained growth and adoption in the consumer electronics market.a

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