CAD CAM

AUTOMATED DEFECT DETECTION SYSTEM

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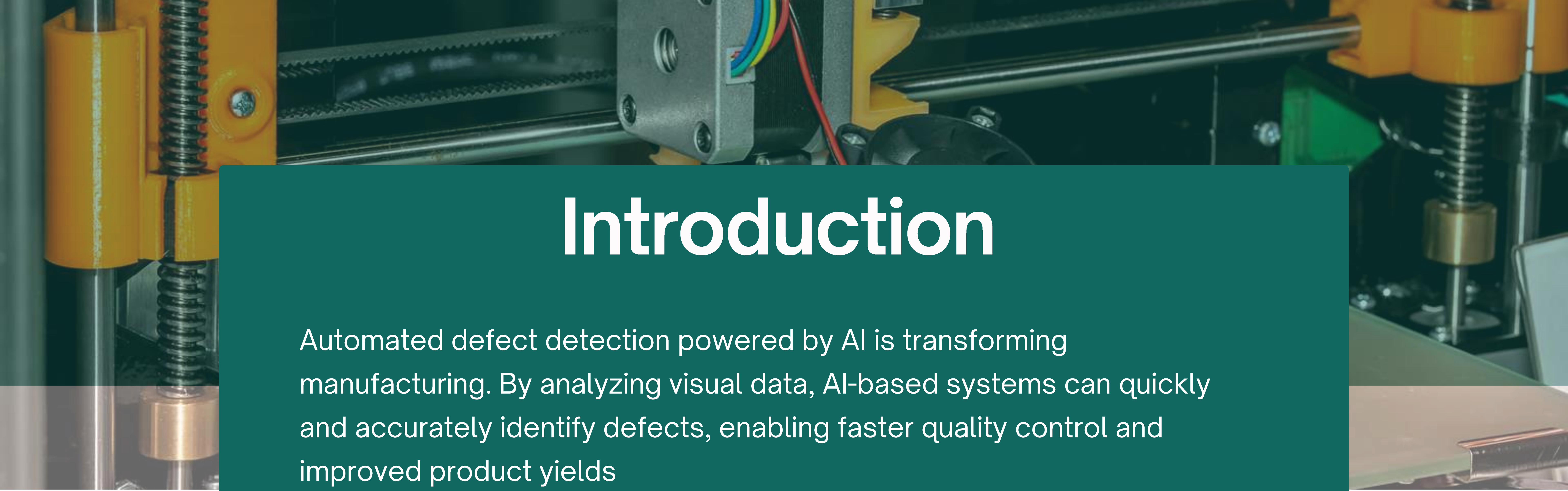


Introduction

Automated defect detection powered by AI is transforming manufacturing. By analyzing visual data, AI-based systems can quickly and accurately identify defects, enabling faster quality control and improved product yields

3D PRINTING

Additive manufacturing is a process of joining materials to 3D model data to make objects, which usually proceeds layer by layer

Printing defects

Overfill, underfill, surface roughness, and warping

Fused Deposition Modelling

A material extrusion technique in which a thermoplastic material is melted and extruded through the hot end to create printed layers

Challenges in Traditional Defect Detection Methods

Human Error
Slow Processes
Subjective Evaluations

Since traditional process optimization usually involves iterative experiments, the experimental process is both time-consuming and expensive An increasing number of research efforts are combining Machine learning with field monitoring.

Process data is monitored and recorded by placing sensors and cameras on the production site

PAST RESEARCH

Song used thermocouple sensors to record thermal timing data from a build platform and used the K-nearest neighbors (KNN) algorithm to predict the warping phenomenon in the FDM process. However, the classification accuracy was only 84% and was not compared with other related algorithms

Westphal and Seitz used a transfer learning approach to experiment with image datasets in combination with an adaptive classifier for the analysis of the part manufacturing process The developed closed-loop system has 85% defect classification accuracy and can adjust the process parameters in time. However, the limited coverage of the microscope used to monitor the printing process in the experiment limits the identification of more other types of surface defects.

PAST RESEARCH

Charalampous developed an ML method that is based on a regression algorithm to investigate the dimensional deviations of CAD models and solid parts.However, this analysis method only evaluates the measurement of printing results and ignores the mechanical movements and thermal changes inside the printed part during production

A laser-based online machining monitoring system was proposed by **Lyu and Manoochehr**i .hey used a model called VGG16 to identify any anomalies happening within the layers They also used a method called PID online closed-loop controL.. However, the complex ML method resulted in relatively high computational costs and a long analysis time.

Petrich . developed a neural network that ingested multimodal sensor data from cameras, microphones, and machine logs to detect defects in laser powder bed fused AM parts with 99.9% accuracy .

In this presentation , defect classification method for FDM processes is proposed for defect diagnosis by fusing the prediction results of two machine learning models. By fusing vision- and sensingbased methods, the classification accuracy is significantly improved compared to the classification of defects in the FDM process using the two methods alone. The accuracy is about 97.9%

MATERIALS NEEDED

SENSOR, 3D PRINTER AND IMAGE RECORDER

- 3D PRINTER : ACCUCRAFT I250D
- AOMEKIE USB MICROSOPE
- IR SENSOR & ACCELEROMETER

Sensor specification	Measurement	Sampling frequency
IR temperature sensor (GY-614V3)	Melt pool temperature	5 Hz
Accelerometer (ADXL357)	Extruder vibration	20 Hz

TABLE 2: Process parameters setting in experimental studies.

Process parameter	Unit	Parameter combination				
		Regular parameters	For high *R*	For low *R*	For high *V*	For low *T*
Extruder temperature (*T*)	°C	220/250	220/250	220/250	220/250	190
Print speed (*V*)	mm/sec	60	60	60	120	60/120
Materials flow rate (*R*)	%	100	150	50	100	100
		Constant parameters over all printing conditions				
Infill	%	100				
Layer thickness	mm	0.3				
Build platform temperature	°C	60				

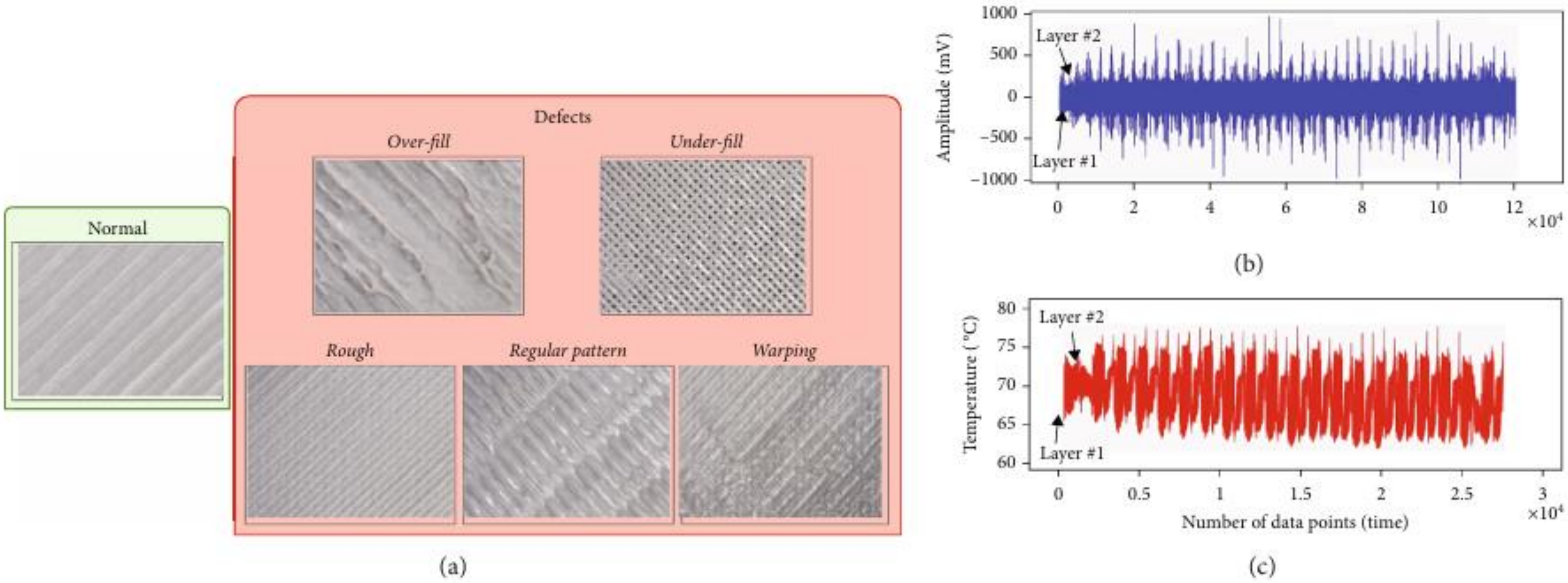


FIGURE 2: Visualization of multimodal data: (a) surface images of the printed part; (b) extruder vibrations (X direction); (c) IR temperature.

MACHINE LEARNING MODELS

We can use three machine learning algorithms from the three algorithms that we found with the help of research papers and books available online.

01

VISION BASED DEFECT CLASSIFICATION

02

TIME SERIES DATA CLASSIFICATION

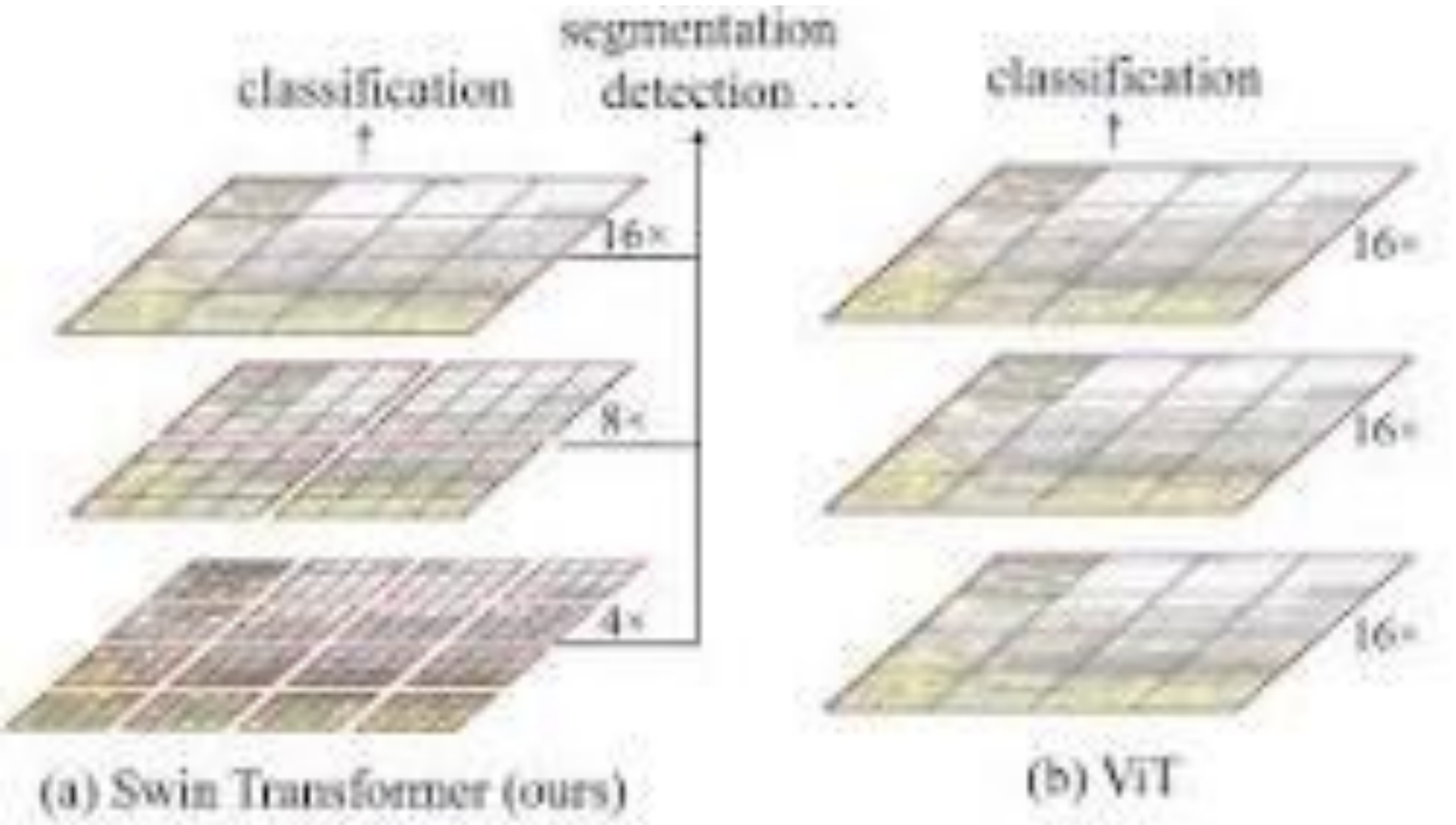
03

COMBINATION OF VISION AND SENSING

VISION BASED DEFECT CLASSIFICATION ALGORITHM

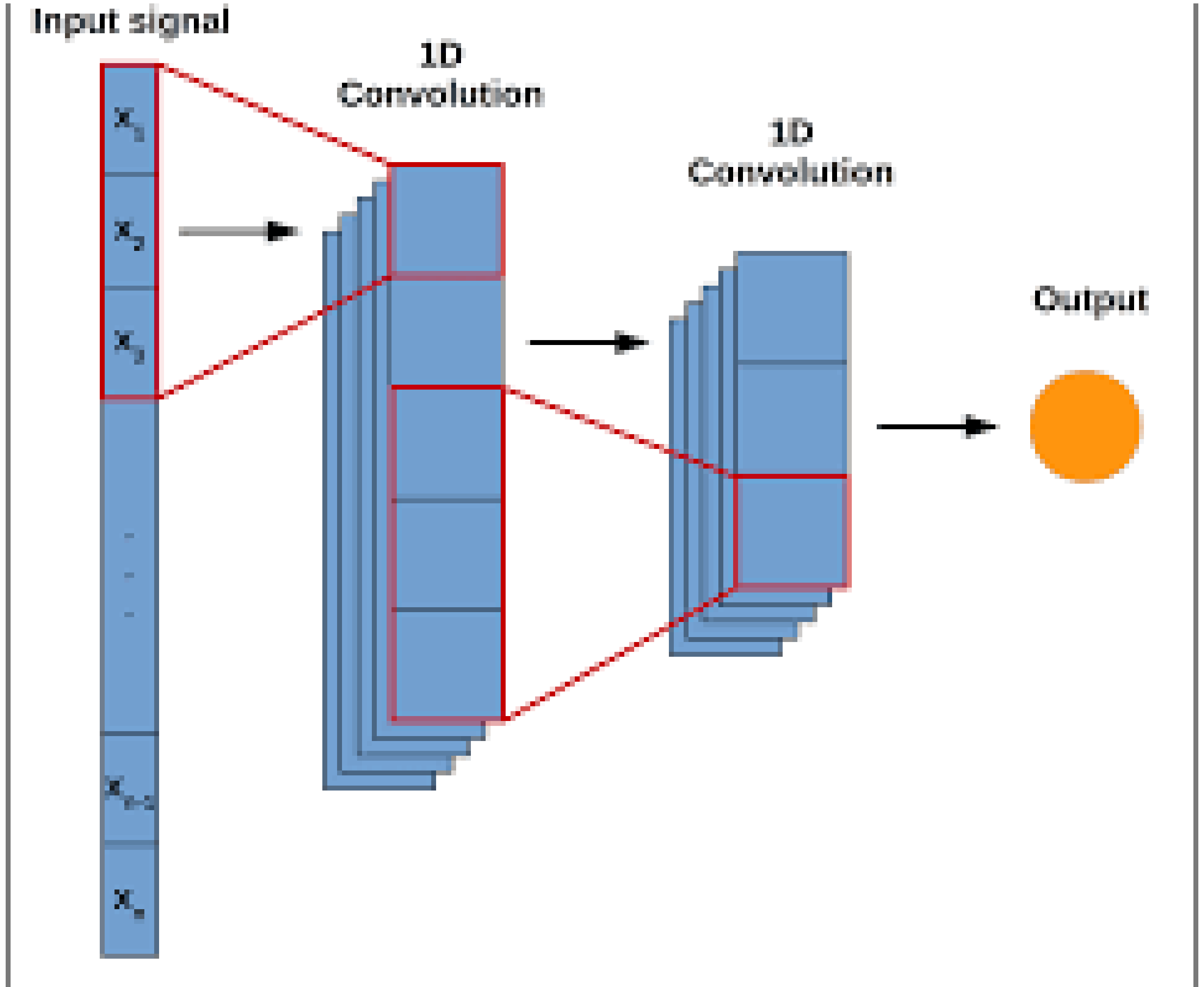
- SWIN TRANSFORMER
- USE OF A SW-MSA THAN MSA : W-MSA + SW-MSA
- TRANSFER LEARNING

- Thus, we use a swin transformer model at 224 X 224 resolution.
- The loss function : SparseCategoricalCrossentropy
- Adam Optimizer



TIME SERIES DATA CLASSIFICATION ALGORITHM

- 1DCNN model to take care of extruder temperature and vibration during the FDM process.



COMBINATION OF VISION AND SENSING

Fuse both the method of vision based defect classification and time series data classification

STEPS

- Pimg(v) = Pimg(1) Pimg(2).............Pimg(p)

Pimg,i represents the probability of the test vector v for the class of i and n is the total number of classes.

- Psen(s) = Psen(1) Psen(2) ⋯, Psen(n) represents the class probability of the sensing signal feature vector based on the sensing signal classification prediction.
- P = (P1,P1,⋯,Pn) = (Pimg,1 +kj ∗Psen,1, Pimg,2 + kj ∗Psen,2, ⋯, Pimg,n + kj ∗Psen,n)

STEPS

- Finally, the class label C predicted by fusion is given by the following equation :

$$C = \frac{\left(\underset{i=1\cdots n}{\arg\max}(P_i)\right)}{2}.$$

- Finally, the class label C predicted by fusion is given by the following equation :

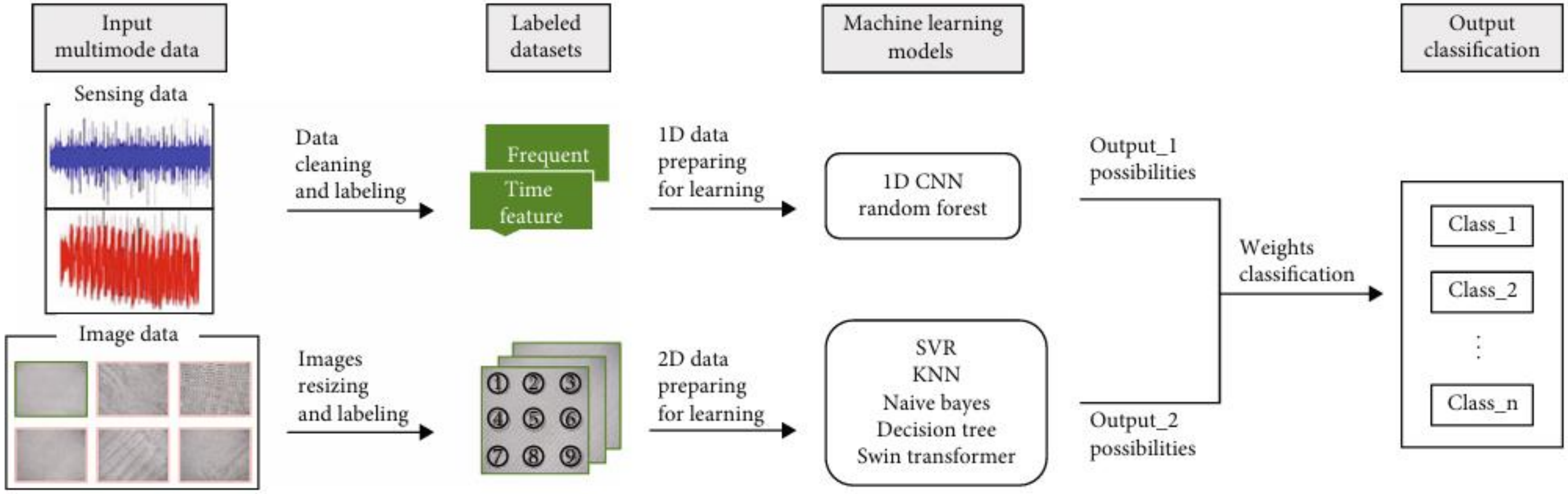
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}},$$

$$\text{Macro average precision} = \frac{\sum_{k=1}^{K} \text{TP}_k / (\text{TP}_{k^*} + \text{FP}_k)}{K},$$

$$\text{Macro average recall} = \frac{\sum_{k=1}^{K} \text{TP}_k / (\text{TP}_{k^*} + \text{FN}_k)}{K},$$

$$\text{Macro } F1\text{-score} = 2^{*}\left(\frac{\text{macro average precision}^{*}\,\text{macro average recall}}{\text{macro average precision}^{-1} + \text{macro average recall}^{-1}}\right). \quad (3)$$

Project Timeline



RESULTS

Image Classification Results.

Swin Transformer model

Experiments	Model	Confusion matrix						Accuracy	Macro avg precision	Macro avg recall	Macro avg $F1$-score
		15	0	0	0	0	0				
		0	0	0	0	0	0				
	SW	0	0	25	0	0	0	0.899	0.794	0.833	0.811
		0	15	0	48	0	0				
		0	0	0	0	30	0				
		0	0	0	0	0	15				
		12	0	0	0	0	3				
		1	7	0	7	0	0				
	SVM	0	0	24	1	0	0	0.899	0.794	0.833	0.811
		0	4	3	41	0	0				
		0	0	0	0	30	0				
		4	1	0	0	0	10				
		15	0	0	0	0	0				
		1	6	1	6	0	1				
Image classification	DT	0	0	23	2	0	0	0.75	0.704	0.707	0.402
		0	7	3	36	0	2				
		0	0	0	0	30	0				
		2	0	0	10	0	3				
		13	0	0	0	0	2				
		3	3	5	4	0	0				
	KNN	1	0	22	2	0	0	0.777	0.723	0.746	0.706
		3	2	5	38	0	0				
		0	0	0	0	30	0				
		4	0	0	2	0	9				
		1	0	3	11	0	0				
		0	1	5	9	0	0				
	NB	0	0	25	0	0	0	0.635	0.484	0.678	0.429
		0	0	11	37	0	0				
		0	0	0	0	30	0				
		0	0	3	12	0	0				

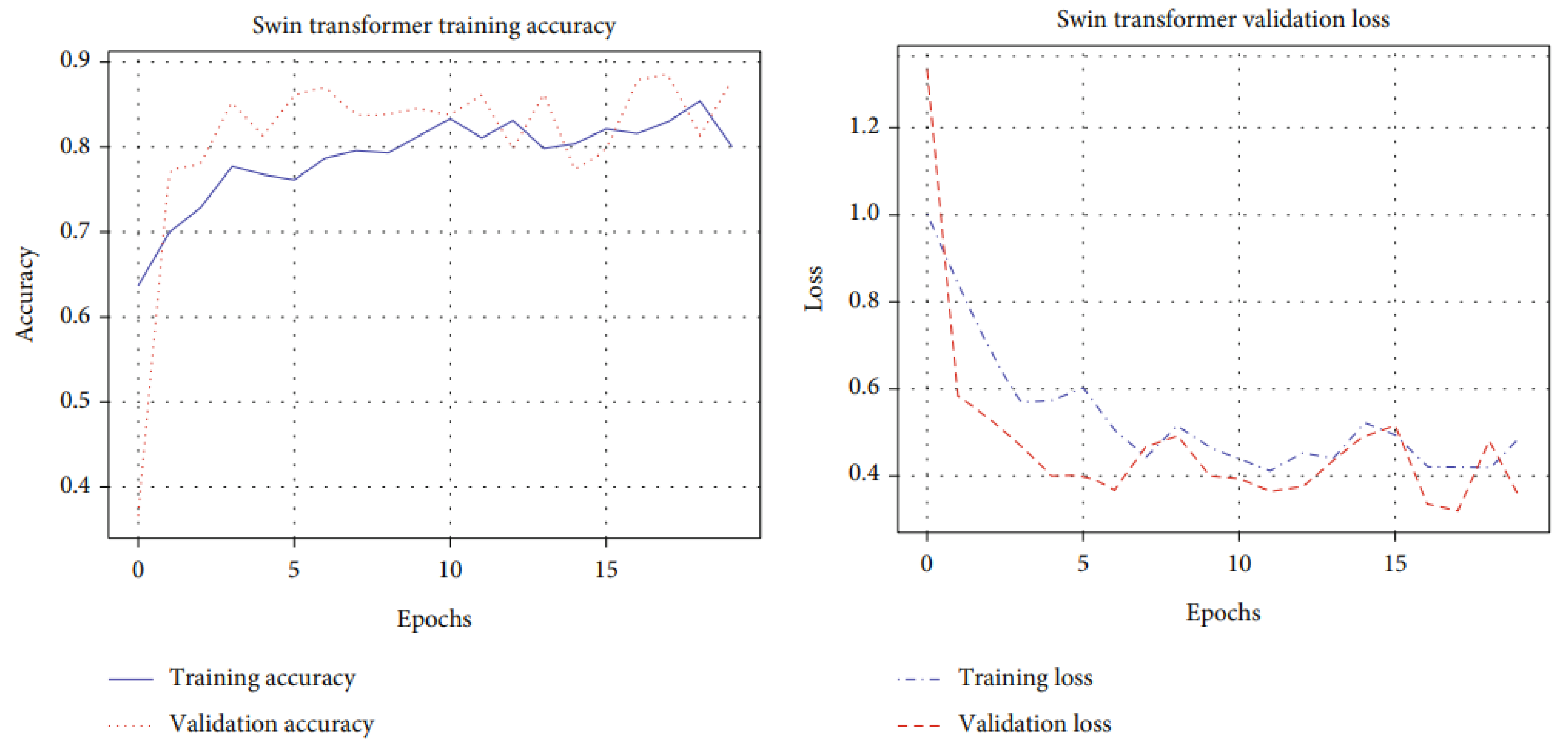


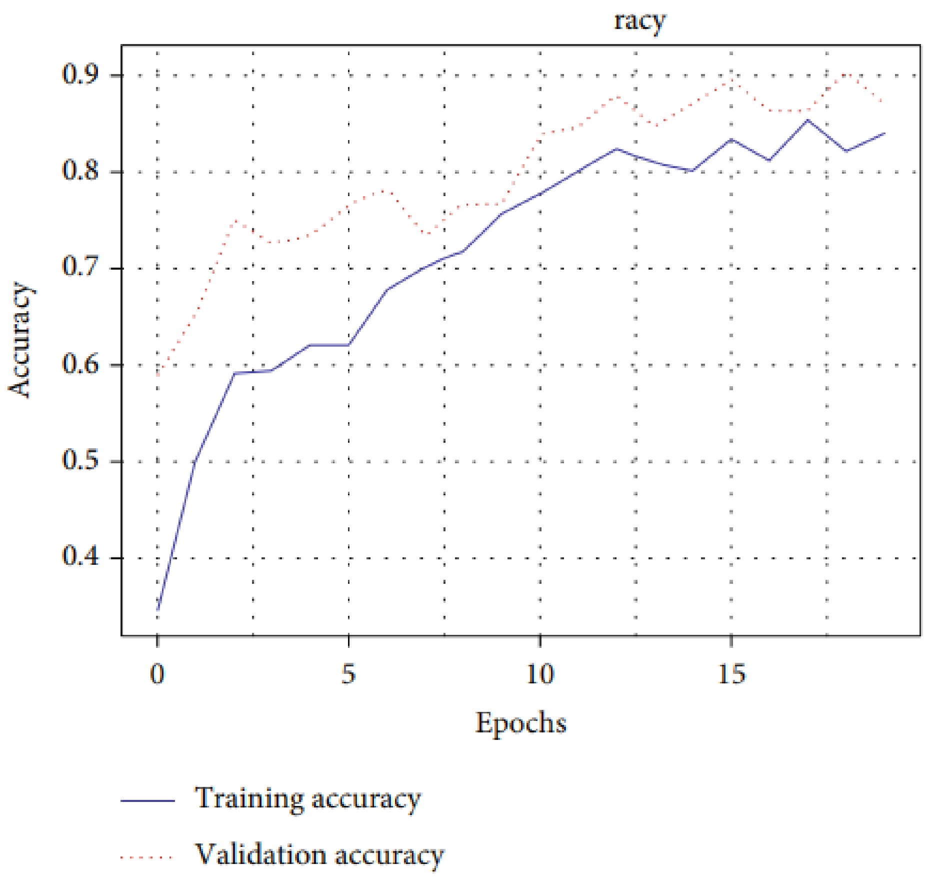
FIGURE 4: Visualization of accuracy and loss of Swin Transformer model on training and validation sets.

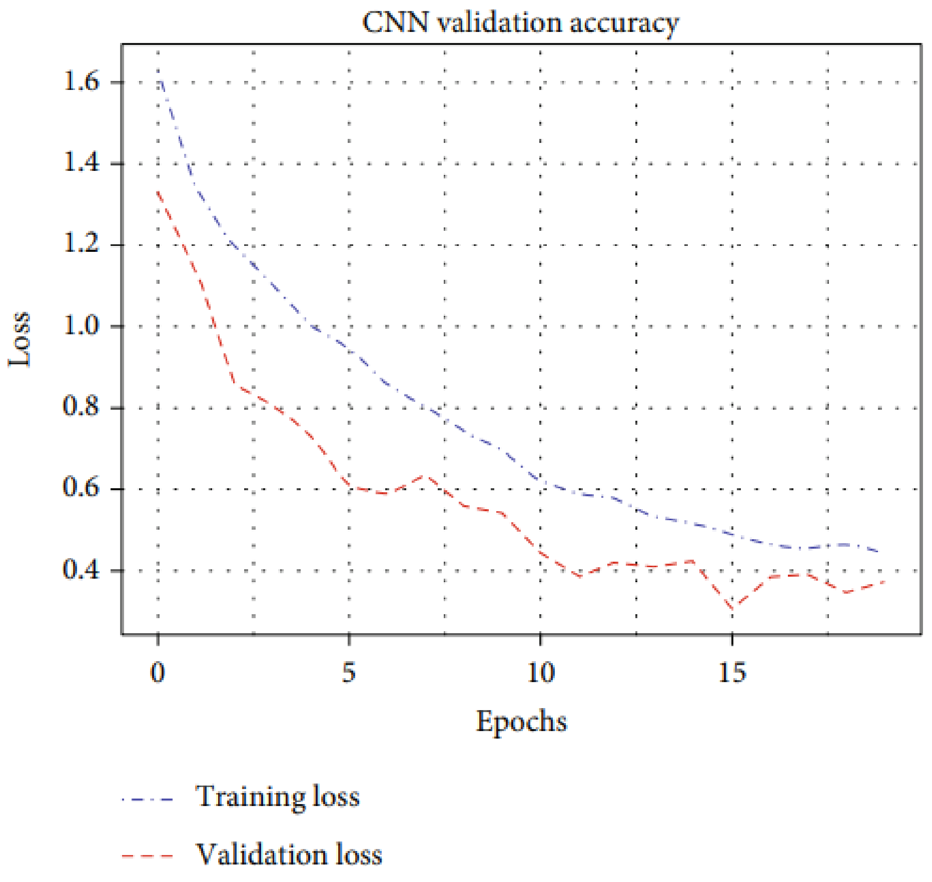
Sensing Data Classification Results.

Table 6: Performance metrics on sensor-based machine learning model test sets.

Experiments	Model	Confusion matrix						Accuracy	Macro avg precision	Macro avg recall	Macro avg $F1$-score
Sensing classification	CNN	10	0	0	0	0	5	0.892	0.901	0.885	0.87
		0	15	0	0	0	0				
		0	0	23	2	0	0				
		0	6	1	39	2	0				
		0	0	0	0	30	0				
		0	0	0	0	0	15				
	RF	15	0	0	0	0	0	0.858	0.881	0.899	0.862
		5	10	0	0	0	0				
		0	0	25	0	0	0				
		11	0	0	36	1	0				
		4	0	0	0	26	0				
		0	0	0	0	0	15				

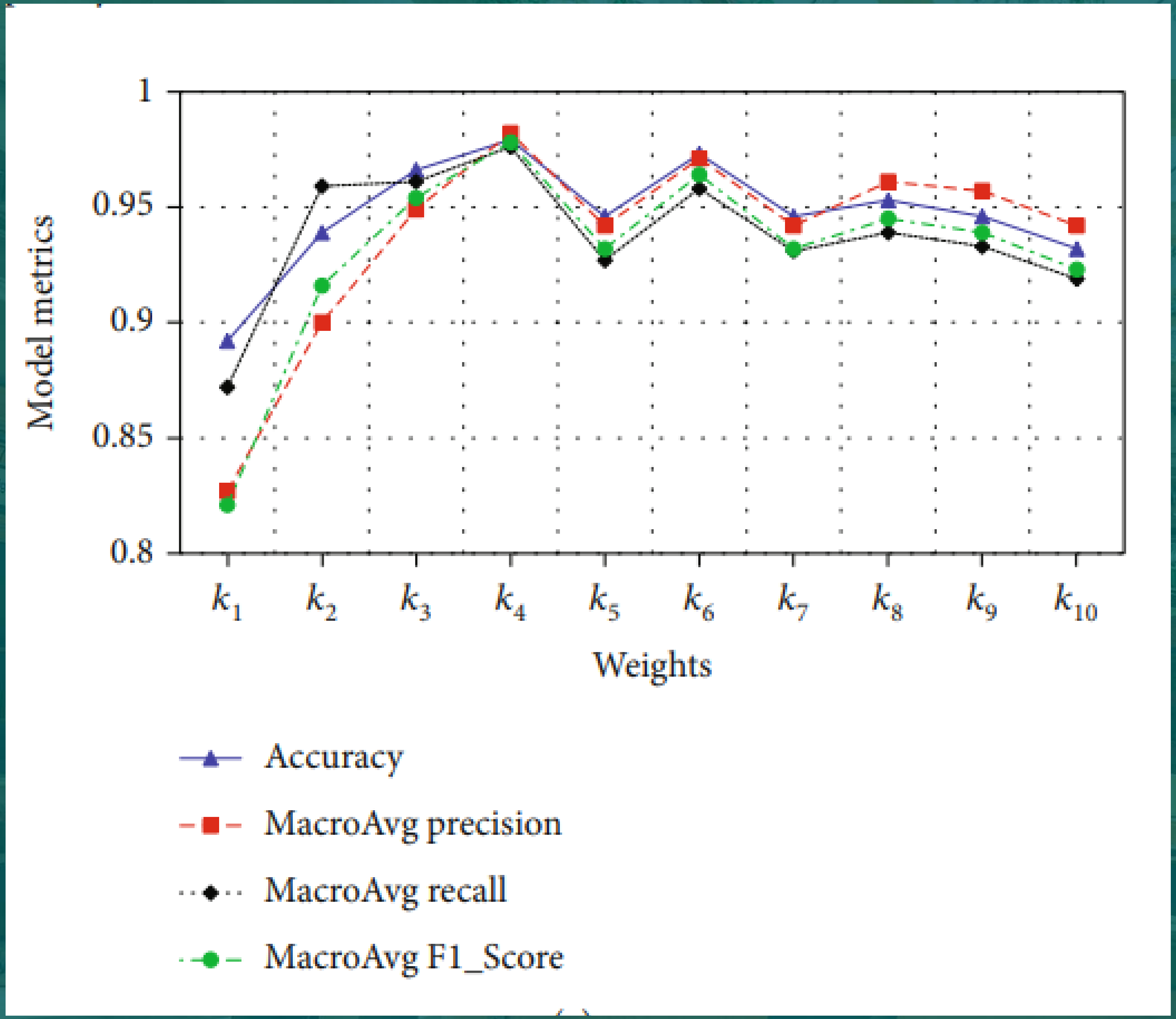
1DCNN model



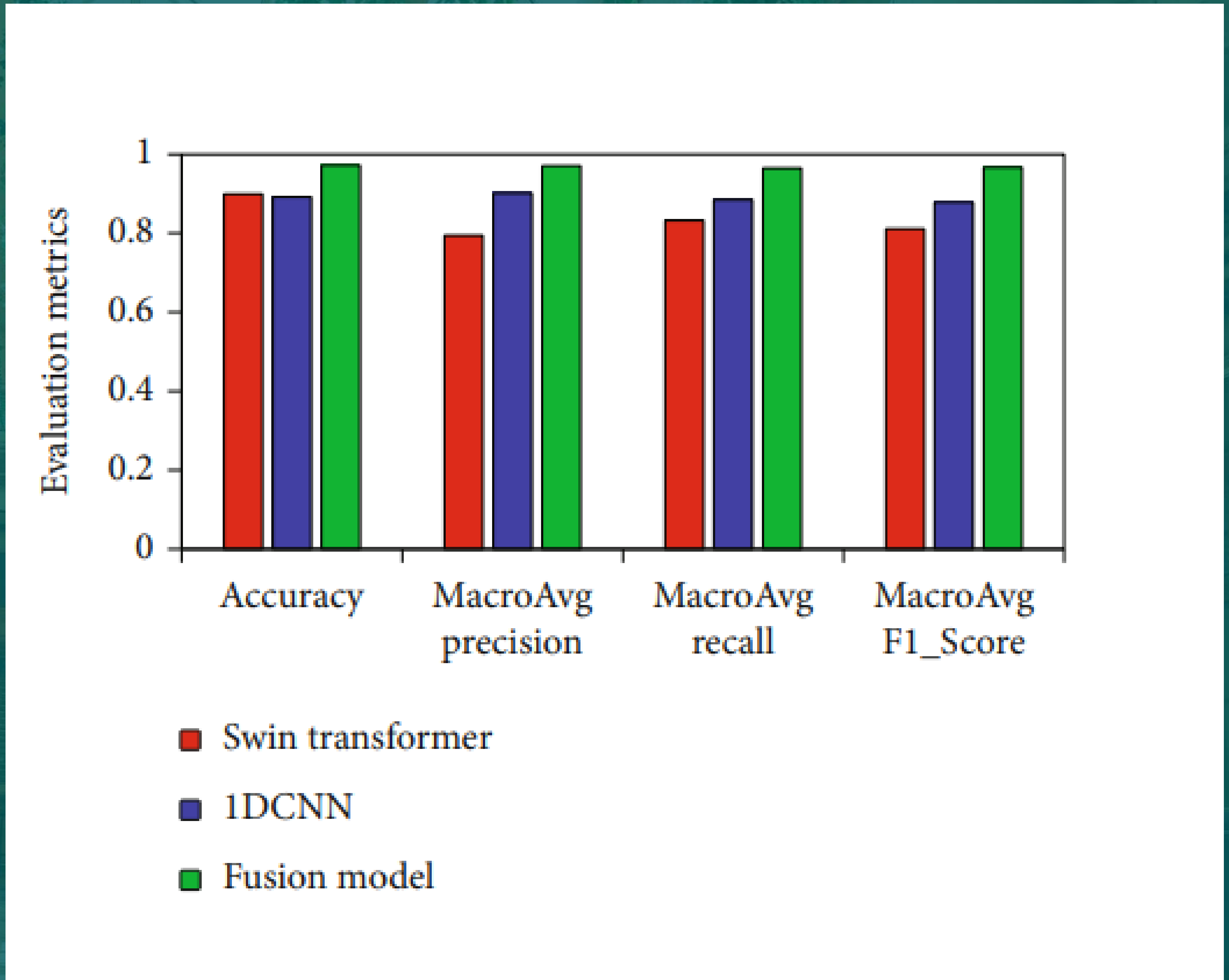


FUSION MODEL.

Prediction performance of fusion model under different weights.



Comparison of evaluation indexes of Swin Transformer,1DCNN, and fusion model on the test set.



Overall the evaluation metrics of the fusion model are higher than those of the Swin Trans?former model and the 1DCNN model, and the metrics are in close agreement, which indicates that the fusion model has good robustness

The fusion model successfully classified various surface defects in the printed parts into six types based on printing quality.

- Rough
- Warping
- Regular Pattern
- Over-Fill
- Under-Fill

According to the classification results of the fusion model, the defect types can be correlated with the root cause to find the process parameters corresponding to them.

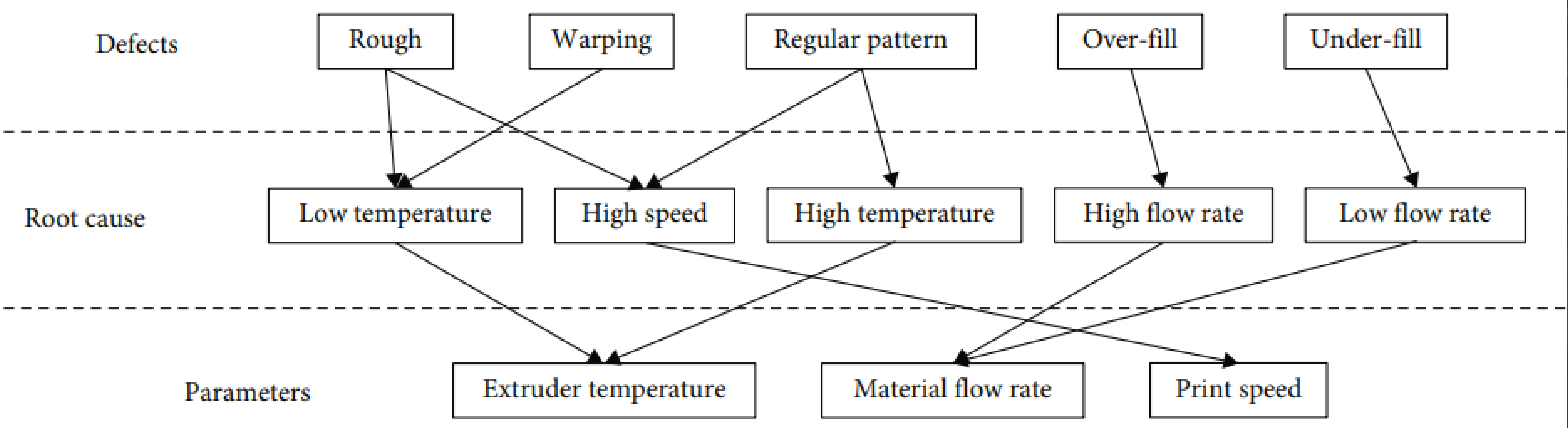


FIGURE 9: The causal relationship between defects and process parameters.

Conclusion

In this study, we proposed a method to improve defect detection in 3D printing. We combined vision-based and sensor-based techniques to diagnose printing issues.The fused model performed better, with over 8.9% and 9.8% higher accuracy compared to individual models. Overall, the experiments demonstrated that machine learning is a promising solution for detecting surface defects in 3D printing and adjusting printer settings accordingly.

References

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