LEVERAGING DEEP LEARNING TECHNOLOGY FOR ENHANCING PRINTING PRESS QUALITY

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ABSTRACT

The use of machine learning techniques for printing quality control has not yet been widely adopted by most printing houses in Nigeria. Whereas deep learning technology can be used to improve printing quality. This study was designed to leverage deep learning technology for defect-detection in newspaper to improve printing quality. Six hundred newspaper images were loaded into a PyCharm programming environment for data exploration, cleaning, pre-processing, and augmentation. The MATPLOT library was used to analyse the visual characteristics of random samples from the image dataset. A four-hundred newspaper-images were selected, which were divided into 320 (160-defective+160 non-defective) for training, and 80 (40-defective+40 non-defective) for validation and testing. The Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Gaussian filters, Local Binary Patterns (LBP), pre-trained Visual Geometry Group sixteen (VGG16) models, Neural Network Search (NNS), and Deep Forest Models (DFM) were used for defect-detections. The CNN achieved acceptable performance in image feature extraction for defect detection, with a validation accuracy of 66.7%. The machine learning ensemble classifiers of Gaussian filter+ LBP + SVM, CNN + SVM, simple CNN, transfer learning with VGG16, and NNS gave training accuracy of 97.3, 71.5, 72.5, 81.3, and 82.3%, respectively. These results demonstrate the effectiveness of various machine learning techniques for defect detection in newspaper images. The Gaussian filter+LBP+SVM model achieved highest accuracy, while its precision, recall and F1 score were 90.3, 89.4, and 85.9%, respectively. The printing press can leverage on deep learning models to improve quality of the newspaper printing.

Index words: Deep learning, Defect detection, Quality control, Newspaper industry.

I. INTRODUCTION

The increase in demand in printing industry for quality makes it necessary to research other techniques and methods that can replace the traditional way of defect detection that requires human visual inspection. Deep learning is a subset of machine learning and Artificial Intelligence (AI) that involves training artificial neural networks to learn from data, which is inspired by the structure and function of the human brain, specifically the way neurons communicate with each other. Deep learning has become a powerful tool for industries, enabling the analysis of large, complex datasets and facilitating decision-making processes that are often more accurate than those generated by humans. The growth of deep learning technology

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is driven by the availability of big data, advances in neural network architectures, and powerful computing hardware.

Automation refers to the use of technology or computers to eliminate human involvement in tasks, thereby making work faster, easier, and reducing errors. Automation is a growing domain and computer programs such as deep learning algorithms are being developed to learn patterns from existing or historical data for better prediction and thereby enhance robust decision-making. This involves the use of systems, computer algorithms, or software to automate repetitive and monotonous tasks within organisations. Most printing press in Nigeria are yet to adopt deep learning technology to assess quality of printing for identification of defects or errors in printing processes.

Quality control is a mechanism by which printing press can attain the required specifications according to the regulatory body and customer expectations. It is concerned with making things factual rather than discovering and rejecting the printings. Deep learning technology has gained much applicability in almost every aspect of life due to its immense potential and capability to learn hierarchical features from various types of data, e.g., numerical, image, text, and audio, which made it a powerful tool in solving recognition problems (Wang et al., 2020), thereby, enabling continuous quality improvement. Deep learning is being used in numerous industries like health, pharmaceuticals, Information Technology (IT), and manufacturing. However, the use of deep learning technology in printing industry in Nigeria is not yet common. Hence, there is need to explore how leveraging on deep learning technology can enhance printing press quality in Nigeria.

II. MATERIAL

The use of X-ray Computed Tomography (XCT) to understand nondestructive evaluation of the Additively Manufactured (AM) parts impact on process parameters and quantifying the built part was found challenging. Hence, a deep learning network was trained using CAD models to experiment data obtained from XCT of an AM Jet engine turbine blade, which revealed promising preliminary results. Also, machine learning can be leveraged to obtain latest high-performance metamaterials and optmised topological designs. The delay in printing high-quality parts using bottom-up stereolithography was resolved using deep learning network (Khadilkar et al., 2019; Wang et al., 2020; Ziabari et al., 2021). Machine learning technology encouraged actionable intelligence through processing of collected data, thereby increasing manufacturing efficiency without noticeable difference in the required resources of humans or materials (Rai et al., 2021). The techniques of machine learning are being used to detect and prevent hacker threats in cybersecurity by leveraging on its data-driven styles to analyse large amount of information, detecting patterns and anomalies showing malicious activities (Shah, 2021). Lawson et al. (2021) stated that machine learning granted researchers a distinct chance in metabolic engineering for more predictability by leveraging omics data and improved production. Machine learning technology used an alogrithm that is able to learn autonomously through the direct data inputted (Bertolini et al.,2021). Zhang et al. (2019) applied Deep Convolutional Neural Network (DCNN) to classify printing defect into crystal, point, no printing, smears, overprinting, trailing, paper powder, and ink. The DCNN applied achieved 96.86% classification accuracy, compared to the deep transfer learning method, however, when combined the DCNN and SVM+SMOTE there was a 20% accuracy improvement. Dhanawat (2022) employed advanced algorithms and analytical knowledge of machine learning to discover intricate landscape of

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anomaly detection within blockchain transactions, which performed accurately and efficiently in anomaly detection. Villalba-Diez et al. (2019) showed possibility of combined deep learning soft sensor application with high resolution optical quality control camera to increase quality accuracy and reduced amount of industrial visual inspection during printing process. Samepedro et al. (2021) observed that devices used in 3D printing do encounter undetected errors and problems, which can cause severe damage to the printer and resulted in output rejection. Therefore, the researchers evaluated different types of deep learning techniques like Multilayer Perception (MLP), Long Short Term Memory (LSTM), and Combine Convolutional Neural Networks (CNN) and LSTM, yet, application of the LSTM was found to be the best. In a combination of deep learning and brain computer interface for 3D where collected data were preprocessed in a MATLAB environment, thereafter used to train various neural network architectures, it was found that CNN-LSTM served the purpose of classfying objects accurately (Kachhia et al., 2020). The present study is using pyCharm programmed environment for data exploration, cleaning, pre-processing, augmentation, while MATPLOT library was used to analyse visual characteristics of loaded random sample image-dataset. Yao et al. (2024) considered conductivity and physical defects in refined print line quality, therefore, a model for defect detection was built using neural architecture and within 4.6ms the model detected an image with an accuracy of 95.5%. Tsai et al. (2019) identified unlawful tappering of printed documents, fake currency, and copyright violation to develop an efficient and safe testing instrument to know source of printed materials using CNN of deep learning capable of learning features automatically and found that feature based support vector machine performed better than deep learning system. The CNN fault diagnosis adopted in printer using 3D to detect and categorise glitches in printing revealed significant precision using secondary data, while support vector machine (5.1%) and artificial neural network (25.7%) provided less precision results compared with the CNN (Verana et al., 2021). Im et al. (2022) suggested that bias can occur in analysing images because classification of images require expertise, therefore, developed a deep learning classification systems, which was found to achieve good results. Hence, in this present study deep learning technology is being leveraged for quality printing in newspaper industry in Nigeria.

III. MEHODS

Through data exploration and visualisation of 600 sample images of printed newspaper, the image data were loaded into pyCharm programming environment. Subsequently, a random sample of the images from the dataset was displayed using a grid from the Matplotslib library to analyse the visual characteristics. The printing paper defects found were smudging, blurring, fading, and colour misregistration. Data cleaning and pre-processing were done by resizing collected images to a standardised size suitable for model input. The input size was set to 256 by 256 pixels to achieve a balance between captured details and minimised scaling operations, in order to convert categorical labels into numerical format, and normalised pixel values to a common scale (e.g., 0 to 1) for consistent model training. Data augmentation was done to prevent over-fitting and enhance generalisation ability of the machine learning models. Transformations such as rotation, flipping, and zooming were applied to ensure variability and diversity in the training data, helping the model better adapt to different patterns. After data cleaning, pre-processing and augmentation of the 400 pages were prepared as dataset for analysis. The dataset was divided into 320 training images (160 defective + 160 non-defective), and 80 (40 defective + 40 non-defective) for validation and testing sets. Training sets were utilised for estimating various parameters and evaluating the performance of the model. The validation set

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was employed during training process to fine-tune model parameters and prevent over-fitting. Upon splitting the data into these sets, a balanced distribution of "defective" and "non-defective" newspapers in each set was ensured. This balance helped to prevent bias and ensured that the model was a representative sample of both defective and non-defective instances during training, validation, and testing. The machine learning techniques employed for defect detection were the Support Vector Machine (SVM), Deep Forest Models (DFM), Convolutional Neural Network (CNN), and ensemble classifiers. The newspaper feature extractions were performed using Gaussian filter, Local Binary Pattern (LBP) and Laplacian of Gaussian filer to denoise images, and extract edges for input into the support vector machine. The Visual Geometry Group sixteen (VGG16), a pre-trained deep learning model, was performed on the ImageNet dataset. The DFM, which comprised cascade and multi-grained forest structures, were used to train the ensemble classifier. These were chosen based on their effectiveness and suitability for this present study. The models leverage ensemble learning techniques to combine predictions of multiple individual classifiers to enhance printing quality in the newspaper industry through deep learning technology. Fig 1. shows the proposed method procedure.

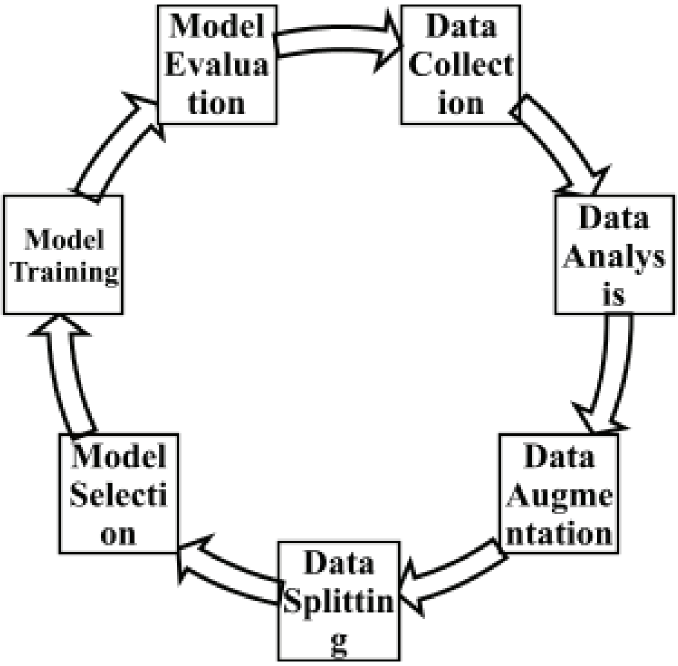

Fig. 1. Proposed method procedure

A. DATA EXPLORATION

This is summarising, visualising, and understanding the main features of the dataset. Its goal was to gain insights into the patterns, distributions, and relationships within the data before proceeding to more advanced analyses or modelling. The visualisation of sample images was done by loading the image data into pyCharm programming environment and subsequently displaying random sample of images from the dataset using a grid from the MATPLOT Library to analyse the visual characteristics.

B. DATA CLEANING AND PRE-PROCESSING

This was done to prepare the dataset for analysis by resizing collected images to standardised size suitable for model input. The input size was set to 256 × 256 pixels to strike a balance between captured details and minimised scaling operations, in order to convert categorical labels into numerical format, and then normalised pixel values to a common scale (e.g., 0 to 1) for consistent model training.

C. DATA AUGMENTATION

This was done to prevent overfitting and enhance the generalisation ability of the machine learning model. Various transformations such as rotation, flipping, and zooming were introduced to ensure variability and diversity to the training data, thereby the model was better adapted to different patterns. This was performed at real time on the Central Processing Unit (CPU), which handles the generation of augmented samples, while the core training operations occurred on the Graphics Processing Unit (GPU).

D. DATA SPLITTING

The obtained dataset was divided into training, testing, and validation sets, which is a common practice in machine learning techniques. Training sets were utilised for estimating various parameters and evaluating the performance of the model. It serves as basis for the model to learn patterns and relationships within the data. Data validation set was employed during the training process to fine-tune model parameters and prevent overfitting. It helped to gauge the model generalisation ability to unseen data, hence, the deep learning model capacity to perform well on new and previously unseen data that were not explicitly trained on. After the training completion, the testing dataset was employed to assess the model performance on completely new and independent data. This step was intended to assess how well the model generalizes to real-world scenarios. By splitting the data into sets, a balanced distribution of "non-defective" and "defective" newspapers in each set was ensured. This balance helped prevent biases and ensured that the model was exposed to a representative sample of both positive and negative instances during training, testing and validation.

E. MODEL SELECTION

The rationale for choosing Convolutional Neural Networks (CNNs) lied in its well-suited architecture for classification tasks, particularly when dealing with structured grid data like images. The CNNs are designed with layers that perform convolutional operations, allowing it to automatically learn hierarchical features from input images. The CNNs has been found to be effective in image classification. Its ability to capture spatial hierarchies and local patterns through convolutional layers made it particularly powerful for tasks where understanding the visual context is crucial. The layered structure of the CNNs enabled it to automatically learn and extract features from images, making it highly effective in discerning patterns and making accurate classifications.

F. MODEL TRAINING

The training phase involved the datasets being introduced into the model that has been labelled or annotated, allowing the model to learn the intricate patterns and relationships present in the data. This learning process involves adjusting the model internal parameters or hyperparameters. In order to optimise the model performance and ensure its ability to generalise well to unseen data, a separate validation set was

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used. The model parameters was fine-tuned based on its performance on validation set. The goal is to minimise the difference or error between the predictions made by the model and the actual target values in the validation set. This iterative process of learning from the training set and refining based on the validation set continues until the model achieves a satisfactory level of performance.

G. MODEL EVALUATION

The trained model was rigorously evaluated using various metrics to gain insights into its overall performance, strengths, and weaknesses. This evaluation was conducted on a separate test set to assess the model ability to generalise. Metrics such as accuracy, precision, recall, and F1 score were employed to provide comprehensive understanding of the model capabilities. In order to assess the model defect detection capabilities, the dataset went through stratified random sampling, creating distinct training, validation and testing sets. The training set was utilised for model training, while validation set determine optimal training epochs and decision thresholds. The test set evaluated the model out-of-sample performance for defect detection.

1. HARDWARE AND SOFTWARE REQUIREMENTS

Computer Processing Unit (CPU): Intel Xeon E5-2680v4 running at 2.40GHz with 14 cores.

Graphic Processing Unit (GPU): NVIDIA Tesla P100 with 16GB of memory, providing significant acceleration for machine learning models.

Random Access Memory (RAM): 128GB, ensuring efficient handling of large datasets and complex models without encountering memory issues.

Operating System: Ubuntu 16.04 LTS, chosen for its stability, compatibility with a wide range of machine learning libraries, and ease of use.

Python Interpreter: Python 3.6.5, the standard language for machine learning and data science, ensuring compatibility with the required libraries.

Gradient boosted Collaborative Forest (gcForest) Library: Version 1.0.9 of the gcForest library, suitable for defect detection tasks and also known for its effectiveness in implementing deep forest models.

Other Libraries: Numpy 1.16.4, Scipy 1.2.1, Scikit-learn 0.20.3, fundamental for data manipulation, scientific computing and machine learning tasks.

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IV. RESULTS AND DISCUSSION

Figure 2. Shows the classification of the 320 newspapers images (160-defective + 160 non-defective) and 80 newspaper images (40-defective and 40 non-defective) to belong to two classes.

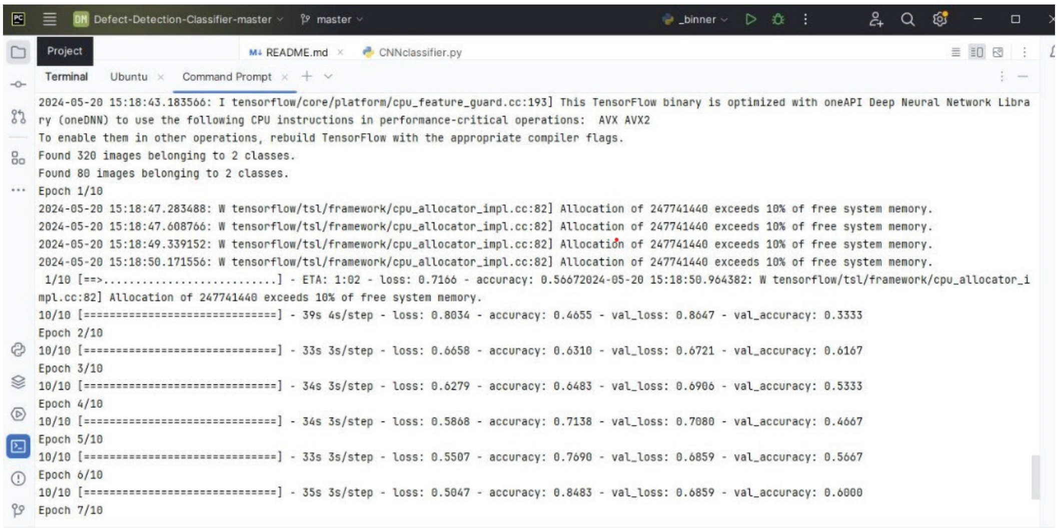

Fig. 2. Defect-Detection classifier

Figure 3. presents results of defect-detection classifiers training loss and accuracy, and validation loss and accuracy. Figure 3. displayed step by step ten epoch for training loss, accuracy, validation loss and accuracy for the 400 newspaper images selected and characterised.

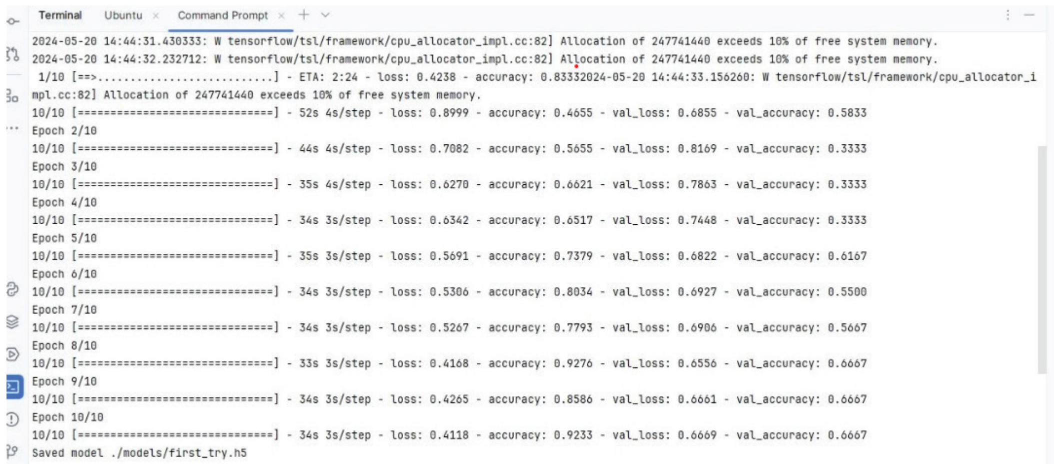

Fig. 3. Defect-Detection classifier result

Table I presents Convolutional Neural Network (CNN) architecture over 10 epochs of trained and validated data for deep learning model and achieved a training accuracy of 88% and a validation loss and accuracy balanced at 67%. The loss values for both trained and validated datasets decreased gradually over the 10 epochs, which indicated that the model learnt the features of the dataset. The validation accuracy started from 32% and improved to 67%. The training loss decreases from 1.14 to 0.46 over the 10 epochs, which was a good indication that the model was learning. This represents a reasonable improvement based on the data used in the present study.

TABLE I
CONVOLUTION NEURAL NETWORK MODEL TRAINING AND VALIDATION ACCURACY RESULTS

Epoch	Training loss	Training accuracy	Validation loss	Validation accuracy
1/10	1.14	0.47	0.81	0.32
2/10	0.86	0.53	0.67	0.73
3/10	0.68	0.68	0.72	0.33
4/10	0.65	0.68	0.72	0.35
5/10	0.61	0.73	0.71	0.38
6/10	0.55	0.82	0.70	0.48
7/10	0.58	0.81	0.69	0.60
8/10	0.53	0.80	0.67	0.65
9/10	0.51	0.84	0.66	0.67
10/10	0.46	0.88	0.67	0.67

Table II presents Convolutional Neural Network (CNN) architecture over 10 epochs of trained and validated data for deep learning model and achieved a training recall of 94%. The validation loss, and recall of 64 and 0%, respectively. The loss values for both trained and validated datasets decreased gradually over the 10 epochs, which indicated that the model learnt the features of the dataset. The validation recall started at 1.00 and dropped to 0.00, indicating no improvement over the 9 epochs. However, training recall increases from 0.34 to 0.94 over the 10 epochs, which indicated that the model was learning.

TABLE II
CONVOLUTIONAL NEURAL NETWORK MODEL TRAINING AND VALIDATION RECALL RESULTS

Epoch	Training loss	Training recall	Validation loss	Validation recall
1/10	1.07	0.34	0.94	1.00
2/10	0.74	0.43	0.66	0.00
3/10	0.65	0.54	0.65	0.00
4/10	0.61	0.67	0.63	0.00
5/10	0.61	0.64	0.63	0.00
6/10	0.54	0.82	0.64	0.00
7/10	0.52	0.81	0.64	0.00
8/10	0.48	0.85	0.64	0.00
9/10	0.45	0.92	0.63	0.00
10/10	0.44	0.94	0.64	0.00

Table III presents Convolutional Neural Network (CNN) architecture over 10 epochs of trained and validated data for deep learning model and achieved a training precision of 71%, and validation loss, and precision of 73 and 33%, respectively. The loss values for both trained and validated datasets decreased gradually over the 10 epochs, which indicated that the model learnt the features of the dataset. The

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validation precision started from 0.00% and rises to a steady value of 33% over the 10 epochs. However, training precision increases from 0.49 to 0.71 over the 10 epochs, which indicated that the model was learning.

TABLE III
CONVOLUTIONAL NEURAL NETWORK MODEL TRAINING AND VALIDATION PRECISION RESULTS

Epoch	Training loss	Training precision	Validation loss	Validation precision
1/10	1.39	0.49	0.57	0.00
2/10	0.90	0.49	0.89	0.33
3/10	0.75	0.47	0.94	0.33
4/10	0.69	0.59	0.89	0.33
5/10	0.70	0.58	0.86	0.33
6/10	0.65	0.63	0.84	0.33
7/10	0.63	0.65	0.82	0.33
8/10	0.62	0.64	0.79	0.33
9/10	0.60	0.67	0.75	0.33
10/10	0.58	0.71	0.73	0.33

Table IV presents Convolutional Neural Network (CNN) architecture over 10 epochs of trained and validated data for deep learning model and achieved a training F1 score of 91%. The validation loss, and F1 score of 69% and 23%, respectively. The loss values for both trained and validated datasets decreased gradually over the 10 epochs, which indicated that the model learnt the features of the dataset. The validation F1 score started from 0.50 steady till the 3rd epoch and dropped to 0.19 at 4th epoch, 0.00 from 5 to 8th epoch, at 9th epoch it was 0.58 and dropped to 0.23 at the 10th epoch, indicating that the model effectiveness over the 10 epochs is not steady. However, training F1 score increases from 0.63 to 0.91 over the 10 epochs, which indicated that the model was learning.

TABLE IV
CONVOLUTIONAL NEURAL NETWORK MODEL TRAINING AND VALIDATION F1 SCORE RESULTS

Epoch	Training loss	Training F1 Score	Validation loss	Validation F1 Score
1/10	0.79	0.63	0.76	0.50
2/10	0.69	0.66	0.76	0.50
3/10	0.63	0.76	0.74	0.50
4/10	0.62	0.71	0.71	0.19
5/10	0.58	0.77	0.69	0.00
6/10	0.52	0.87	0.68	0.00
7/10	0.49	0.85	0.67	0.00
8/10	0.47	0.85	0.67	0.00
9/10	0.44	0.91	0.69	0.58
10/10	0.42	0.91	0.69	0.23

Table V presents Gauss filter LBPSVM architecture over 10 epochs of trained and validated data for deep learning model and achieved a training recall of 89%. The validation loss and recall of 91 and 80 %, respectively at 9th epoch. The model training loss decreased gradually over the 9 epochs, while validation loss fluctuated, which indicated that the model learnt the features of the dataset. The validation recall started from 1.00 and decreased gradually from the 5th epoch after few instabilities in the upper epoch, indicating the model detected fewer defects in the printing, while training recall decreases from 0.76 to 0.49 for 1-4 epoch, but increased from 0.64 to 0.89 for 6-10 epochs.

TABLE V
GAUSSFILTER+LBP+SVM MODEL TRAINING AND VALIDATION RECALL RESULTS

Epoch	Training loss	Training recall	Validation loss	Validation recall
1/10	1.52	0.76	0.70	1.00
2/10	0.69	0.82	0.69	0.00
3/10	0.68	0.44	0.69	0.03
4/10	0.69	0.49	0.69	1.00
5/10	0.62	0.68	0.63	0.92
6/10	0.63	0.64	0.68	0.98
7/10	0.54	0.81	0.67	0.83
8/10	0.38	0.82	0.73	0.83
9/10	0.35	0.84	0.91	0.80
10/10	0.29	0.89	0.82	0.63

Table VI presents GaussfilterLBPSVM architecture over 10 epochs of trained and validated data for deep learning model and achieved a training precision of 90%, and average validation loss, and precision of 73.50% and 66.60%, respectively.

TABLE VI
GAUSS FILTER + LBP + SVM MODEL TRAINING AND VALIDATION PRECISION RESULTS

Epoch	Training loss	Training precision	Validation loss	Validation precision
1/10	2.18	0.42	0.70	0.00
2/10	0.70	0.58	0.69	0.58
3/10	0.70	0.61	0.69	0.83
4/10	0.67	0.63	0.68	0.64
5/10	0.62	0.68	0.62	0.69
6/10	0.61	0.69	0.69	0.78
7/10	0.48	0.73	0.95	0.72
8/10	0.43	0.82	0.77	0.77
9/10	0.35	0.81	0.76	0.74
10/10	0.41	0.90	0.80	0.61

Table VII presents Gauss filter LBPSVM architecture over 10 epochs for F1 Score. The F1 score starts at 0.38 in the first epoch and improves significantly, reaching 0.86

by the 10th epoch. This indicates that the model is getting better at handling both precision and recall for the training data, leading to an overall improved performance in detection. The loss consistently decreases, starting at 1.21 in the first epoch and reaching 0.30 by the last epoch. A decreasing loss is a positive sign, indicating that the model is learning and fitting the training data better over time. The F1 score on the validation set starts at 0.00 in the first epoch, suggesting that the model was initially unable to generalize well on unseen data. By the second epoch, the validation F1 score jumps to 0.43 but fluctuates in the subsequent epochs. After reaching a peak around 0.46 in the fourth epoch, the F1 score starts declining until 0.29 by the 10^{th} epoch. The drop in validation F1 score suggests that the model is likely overfitting but performs well on the training data, while model struggles to generalize to the validation set. The validation loss initially decreases slightly, reaching a low point in the third epoch but starts to increase steadily from the 4^{th} epoch at 0.68 to 1.16 in the final epoch. The increase in validation loss, along with the drop in the F1 score indicates overfitting, however, the Gauss filter + LBP + SVM model is learning patterns well from the training data. Nevertheless, in order for the model to generalise to the unseen data there is needs for more data for the training of the model to be applied in a large-scale printing industry apart from this present study on one stop shop printing press.

TABLE VII
GAUSS FILTER + LBP + SVM MODEL TRAINING AND VALIDATION F1 SCORE RESULTS

Epoch	Training loss	Training F1 Score	Validation loss	Validation F1 Score
1/10	1.21	0.38	0.69	0.00
2/10	0.69	0.50	0.68	0.43
3/10	0.67	0.65	0.67	0.36
4/10	0.62	0.68	0.68	0.46
5/10	0.55	0.68	0.70	0.43
6/10	0.51	0.73	0.71	0.41
7/10	0.47	0.80	0.74	0.42
8/10	0.36	0.87	0.88	0.28
9/10	0.31	0.88	0.94	0.30
10/10	0.30	0.86	1.16	0.29

Table VIII presents ensemble classifiers and their training accuracy for newspaper images extracted for evaluation to detect any defection using Gaussian filter plus Local Binary Pattern (LBP), plus Support Vector Machine (SVM) with a radial basis function (rbf) {Gauss filter + LBP + SVM (rbf)}, which achieved an accuracy of 97.3%. The Convolution Neural Network (CNN) + SVM (rbf kernel) achieved an accuracy of 71.3%. Also, simple CNN (3Convolution + 1FC) achieved an accuracy of 72.5%, and transfer learning (VGG16) achieved an accuracy of 81.3%, Neural Network Search (NNS) achieved an accuracy of 82.3%. The NNS technique automatically searched for optimal neural network architecture for a given task compared to manually designed architectures. These results demonstrated effectiveness of different machine learning techniques for defect detection in newspaper images. However, Gauss filter+LBP+SVM (rbf kernel) revealed highest accuracy (97.3%), which means its learning rate was very high compared with other designed architectures.

TABLE VIII
COMPARISON OF ENSEMBLE CLASSIFIERS AND THEIR RECEPTIVE TRAINING ACCURACIES

Classifier	Accuracy
Gauss filter+LBP+SVM (rbf kernel)	97.3%
CNN+SVM (rbf kernel)	71.3%
Simple CNN (3 Conv+1 FC)	72.5%
Transfer Learning (VGG16)	81.3%
Neural Network Search	82.3%

Table IX presents ensemble classifiers and their training precision for newspaper images extracted for evaluation to detect any defection using Gaussian filter plus Local Binary Pattern (LBP), plus Support Vector Machine (SVM) with a radial basis function (rbf) {Gauss filter + LBP + SVM (rbf)}, which achieved precision of 90.3%. The Convolution Neural Network (CNN) + SVM (rbf kernel) achieved precision of 84.0%. Also, simple CNN (3Convolution + 1FC) achieved precision of 71.2%, and transfer learning (VGG16) achieved precision of 88.4%, Neural Network Search (NNS) achieved precision of 90.7%. The NNS technique automatically searched for optimal neural network architecture for a given task compared to manually designed architectures. These results demonstrated precision of different machine learning techniques for defect detection in newspaper images. However, the auto NNS shows precision of 90.7% compared to Gauss filter+LBP+SVM (rbf kernel) of 90.3%. Therefore, the learning technique of auto NNS shows fractional difference to Gauss filter+LBP+SVM (rbf kernel).

TABLE IX
COMPARISON OF ENSEMBLE CLASSIFIERS AND THEIR RESPECTIVE TRAINING PRECISIONS

Classifier	Precision
Gauss filter+LBP+SVM (rbf kernel)	90.3%
CNN+SVM (rbf kernel)	84.0%
Simple CNN (3 Conv+1 FC)	71.2%
Transfer Learning (VGG16)	88.4%
Neural Network Search	90.7%

Table X presents ensemble classifiers and their training recall for newspaper images extracted for evaluation to detect any defection using Gaussian filter plus Local Binary Pattern (LBP), plus Support Vector Machine (SVM) with a radial basis function (rbf) {Gauss filter + LBP + SVM (rbf)}, gave recall of 89.4%. The Convolution Neural Network (CNN) + SVM (rbf kernel) gave recall of 95.6%. Also, simple CNN (3Convolution + 1FC) achieved recall of 93.9%, and transfer learning (VGG16) achieved precision of 90.0%, Neural Network Search (NNS) achieved precision of 97.5%. The NNS technique automatically searched for optimal neural network architecture for a given task compared to manually designed architectures. These results demonstrated recall of different machine learning techniques for defect detection in newspaper images. However, the auto NNS, CNN+SVM, simple CNN, transfer learning, and Gauss filter+LBP+SVM (rbf kernel) shows recall of 97.5, 95.6, 93.9, 90.0, and 89.4%, respectively.

TABLE X
COMPARISON OF ENSEMBLE CLASSIFIERS AND THEIR RECEPTIVE TRAINING CLASSIFIER

Classifier	Recall
Gauss filter+LBP+SVM (rbf kernel)	89.4%
CNN+SVM (rbf kernel)	95.6%
Simple CNN (3 Conv+1 FC)	93.9%
Transfer Learning (VGG16)	90.0%
Neural Network Search	97.5%

Table XI presents ensemble classifiers and their training F1 score for newspaper images extracted for evaluation to detect any defection using Gaussian filter plus Local Binary Pattern (LBP), plus Support Vector Machine (SVM) with a radial basis function (rbf) {Gauss filter + LBP + SVM (rbf)}, Convolution Neural Network (CNN) + SVM (rbf kernel), simple CNN (3Convolution + 1FC), transfer learning (VGG16), and Neural Network Search (NNS) reached F1score of 85.9, 84.0, 91.5, 93.7, and 90.5%, respectively. The NNS technique automatically searched for optimal neural network architecture for a given task compared to manually designed architectures. The transfer learning (VGG16) indicates highest recall (93.7%) compared to other machine learning techniques.

TABLE XI
COMPARISON OF ENSEMBLE CLASSIFIERS AND THEIR RESPECIVE TRAINING F1 SCORE

Classifier	F1 Score
Gauss filter+LBP+SVM (rbf kernel)	85.9%
CNN+SVM (rbf kernel)	84.0%
Simple CNN (3 Conv+1 FC)	91.5%
Transfer Learning (VGG16)	93.7%
Neural Network Search	90.5%

The hyper-parameter search and values for trial runs for the deep learning model were presented in Fig. 4. The image processing pipeline includes a vanilla block for standard convolutional layers. The inputted images were normalized, but not augmented. The convolutional layer in the block used a kernel size of 3, with 1 block and 2 layers per block. Max pooling was applied, but separable convolutions were not used. A dropout rate of 0.25 was applied, while the layer consists of 32 and 64 filters in the first and second layers, respectively. The classification head used a spatial reduction method of flatten, and applied a dropout rate of 0.5. The model was trained using adam optimizer with a learning rate of 0.001. The results from the trial indicated that the chosen hyper-parameters led to promising performance in classifying defects in newspapers.

```
Search: Running Trial #1

Value           |Best Value So Far |Hyperparameter
vanilla         |vanilla           |image_block_1/block_type
True            |True              |image_block_1/normalize
False           |False             |image_block_1/augment
3               |3                 |image_block_1/conv_block_1/kernel_size
1               |1                 |image_block_1/conv_block_1/num_blocks
2               |2                 |image_block_1/conv_block_1/num_layers
True            |True              |image_block_1/conv_block_1/max_pooling
False           |False             |image_block_1/conv_block_1/separable
0.25            |0.25              |image_block_1/conv_block_1/dropout
32              |32                |image_block_1/conv_block_1/filters_0_0
64              |64                |image_block_1/conv_block_1/filters_0_1
flatten         |flatten           |classification_head_1/spatial_reduction_1/reduction_type
0.5             |0.5               |classification_head_1/dropout
adam            |adam              |optimizer
0.001           |0.001             |learning_rate
```

Fig. 4. Hyper-parameter search

A. LIMITATIONS

This present model training was based on small scale data for one stop shop printing press which can be deployed at acquiring small size data for printing quality enhancement, however, for generalisation to large scale printing press for unseen data, more data are needed to train the model to improve its predictions.

V. CONCLUSION

The convolutional neural network deep learning models were shown to be effective in learning and detecting defects in newspaper images. The validation accuracies indicate that the models can generalize reasonably well to unseen data, which is crucial for real-world applications. The combined deep learning ensemble of Gaussian filter plus Local Binary Pattern (LBP) plus Support Vector Machine (SVM) with a radial basis function (rbf) {Gauss filter + LBP + SVM (rbf)}, Convolution Neural Network (CNN) + SVM (rbf kernel), simple CNN (3Convolution + 1FC), transfer learning (VGG16), Neural Network Search (NNS, which is a technique that automatically searched for optimal neural network architecture for a given task compared to manually designed architectures). The results revealed that Gauss filter+LBP+SVM (rbf kernel) was most effective among the different deep learning techniques used for defect detection of the newspaper images. This means that its learning rate was very high compared with other designed architectures of the deep learning technology. The NNS and Gauss filter + CNN + SVM gave highest precision indicating that both avoided false defect detection compared to other models. The auto NNS, and CNN + SVM gave highest recall values meaning that both models could identify nearly all defects with fewer undetected defects in the newspaper images. The F1 score revealed that transfer learning is the best performing model followed by simple CNN, while the Gauss filter + CNN + SVM F1 score indicates that the model did not balance precision and recall very well when it is compared to other models. In a hyper-parameter tuning performed using AutoKeras to optimise the model performance, the best hyper-parameters found during the search process involved using a vanilla block type, normalising the images but not augmenting the data, and using a specific setting for the convolutional layers and optimiser. The hyper-parameter tuning results indicated that the chosen parameters were effective for the newspaper defect detection task. The Gaussian filter+ LBP + SVM deep learning model can be adopted in printing press industry for high quality printing, based on its accuracy. This revealed that printing press can leverage on deep learning technology for enhancing printing quality in the printing press industry.

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