International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

DEFECT IDENTIFICATION IN MOLD PRODUCTS USING DEEP LEARNING TECHNOLOGY

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Abstract——For enhanced productivity and quality, "smart factories" employ various technological solutions. The paper presents a deep learning-based approach for product faults classification in a smart factory environment. In this context, AI-based systems are able to identify the faulty products and remove them from the production line successfully. It functions through several inter-linked modules. The "brain" and central control unit is a Programmable Logic Controller (PLC) that controls and coordinates all the other elements of the system. An AI-integrated board identifies and classifies defective items based on pre-trained Convolutional Neural Network (CNN) models. Transfer learning, applying a model trained on one task to solve a related task, is used for training the models on a GPU server. This allows the possibility of quickly and correctly determining defects in castings.

Keywords: Defective products Classification, Artificial Intelligence, Transfer learning.

INTRODUCTION

The global economic downturn of the past several years has given the manufacturing industry a fresh start. The true value added is the main emphasis. Many businesses that have moved operations to areas with lower labour costs are now working to get back in the game. Powered by four forms of disruptive technology—connectivity, analytics, human-machine communication, and sophisticated engineering—the present period of digital transformation in the production and manufacturing industries is known as Industry 4.0 (I4.0). The last three industrial revolutions were driven by steam, energy, and automation; I4.0 is a continuation of this trend. Smart and effective manufacturing systems are the result of combining data, AI, machines, and communication. The purpose of Industry 4.0, or Industry 4.0, is to pave the way for "smart" factories that may use information and machinery to boost productivity, quality, and patron happiness. Cyber-physical systems for manufacturing (CPPS) are at the heart of Industry 4.0, allowing machines to interact with one another and with humans through the IoT. Sensors in the factory collect information on the manufacturing process as a whole. After collecting this information, it is put into AI algorithms, which then assess the data and make recommendations for improving product quality while keeping costs down. Artificial intelligence will then be used to enhance the factory's productivity. In this study, we discuss how to classify manufacturing defects using just feature data. To automatically identify and categorise damaged items in the product line, characteristics acquired through

sensors and cameras must be used. Because it influences the classification models' efficacy and performance, feature selection is an important stage in this challenge. With the suggested strategy, only the most predictive traits are chosen. We compare our approach to the state-of-the-art on three test data sets spanning multiple industries of manufacturing. With a low feature selection ratio, our technique is able to achieve excellent accuracy, resilience, and immediate performance for feature-based defect classification.[2] However, the inherent error-proneness of feature extraction and classification-based approaches for defect identification in the real world of manufacturing can't be overstated. And they can't be modified for use with a variety of goods and assembly methods. However, deep learning techniques can adapt to new goods and circumstances by learning from massive quantities of data and updating their characteristics automatically. When applied to computer vision applications including image classification, object identification, object recognition, and audio signal processing, deep learning approaches have proven to be quite effective. Thus, there is significant promise for using deep learning techniques to defect identification in industrial settings [5]. One of the key benefits of artificial intelligence methods lies in how they are able to learn and modify new features from various and copious data sources. In order to improve the system's flaw detection capabilities, it must be regularly trained with new data.

I. LITERATURE SURVEY

According to [1] Huy Toan Nguyen et al., "Defective products classification system and smart manufacturing facilities based on deep learning," electronics, Volume 10, Issues 826, March 2021. This study presents a deep learning-powered method for classifying faulty products in smart manufacturing facilities. A cloud service, a PLC module to operate any mechanical equipment, and the embedded AI engine (Jetson Nano hardware) make up the proposed system's three primary components. An AI Edge Module was created by fusing an AI embedded board with a PLC board.

Sensors are devices volume:20, issue:6783, November 2020, Kalsoom T, Ramzan N, Ahmed S, Ur-Rehman M, et al. In this article, we explore the paper's sensor technology. In this article, we looked at the various sensor technologies now in use in "smart factories," which are part of the manufacturing business. The technology-driven smart factory is also the subject of a comprehensive literature study published here. The essential intelligent aspects of a smart factory were identified as sensor utilisation, interoperability of multiple Internet of Things (IoT) devices, integration of robots and AI, and the use of virtual reality (VR) technology. Since sensors play a crucial role in a smart factory, this article breaks down the many types of sensors, as well as their sub-types, identifying their key features, materials, purposes, application domains, benefits, and drawbacks. These tools allow for the seamless sharing of information between businesses, suppliers, and customers, ultimately leading to a product that meets the needs of the market.

Cyber-physical systems are an integral part of the smart factories being built as part of Industry 4.0, as reviewed in [3] Devarpita Sen and Rajarshi Roy et al. After years of

development, cyber-physical systems (CPS) have allowed for the realisation of the fourth industrial revolution, as detailed in this article. With the help of other supporting technologies, CPS closes the gap between industries like manufacturing and IT, resulting in the smart factory, which is having a profound impact on the worldwide market, social life, and the worldwide economy. In addition, if the industrial revolution is successful, it will open the way for better, more strategic management. The article examines CPS in the business world, including its prerequisites (such as technology and managerial abilities), architectures, and desired characteristics.

In the article "Automatic thresholding for identifying flaws by back-ground hdr mode extents," published in the Journal of Manufacturing Systems, Volume 37, Issue 83, October 2015, authors M. Aminzadeh and T. Kurfess, among others, discuss this same topic. A common segmentation approach, automatic thresholding is described in this article for its usage in automated visual examination of flaws. As a result, several strategies for determining the best threshold to use have been presented. These techniques also need previous knowledge of the whole number of thresholding levels, which is not always available in cases when defect identification necessitates bi-level segmentation. This study proposes a novel method for threshold selection, which compares the histogram variations between background data and defective regions in order to identify the threshold value at the border of the degree bands of defect (object) and background. The suggested technique is able to automatically identify problematic regions, as well as background regions that are devoid of defects. Threshold values are chosen automatically at the boundaries of the background summary mode based on the histogram's analysis. On numerous representative examples of surface flaw photos, the suggested technique performed admirably.

KEY TECHNOLOGY

Deep Learning is a component of ML and AI that attempts to simulate the way that people learn new information. Data science includes fields like statistics and predictive modelling, of which deep learning is an integral part. The term "Artificial Intelligence" (AI) refers to the cognitive abilities demonstrated by machines. Using AI, we may create a computer with a virtual intelligence that does a given task as well as a person. We are digitising robots using AI to the point where the robot does all tasks by itself, like a waiter at the dining establishment or a computerised guided vehicles in a factory. It understands basic human language and can distinguish photos that we've trained it to recognise using transfer learning and deep learning techniques.

The faulty goods categorization approach is a deep learning-powered approach to identifying and categorising product flaws. A data collecting component, a flaw detection component, and the defect classification component make up the system's core features. The camera pictures of the products have been taken and preprocessed by the data acquisition module. The defect recognition component employs a convolutional neural network (CNN) to

pinpoint the ROIs in pictures that could be affected by faults. The defect categorization module employs yet another CNN to categorise the identified ROIs as cracks, nicks, stains, and so on. Each image's fault labels and associated ROIs are generated and produced by the system. We chose a webcam webcam with a dimension of 300x300 pixels so that we could get clear shots of the rotating product on the production line. Images classified at this resolution are crisp and detailed enough for accurate analysis. In addition, we made sure that the product line ran slowly so that VFD picture captures would be less prone to blur. Every time the camera takes a picture, it will upload it to a remote service in case more training is required. However, the picture is also used to categorise the product by being put into deep learning pre-trained models. PLC receives the categorization results through SPI interface and uses them to command peripherals. Without touching the hardware, the operator may choose a matching model for each product, re-train the current version with new data, or train a brand-new model using photos of the product.

Sensors, facilities, and cameras set up in manufacturing facilities are used to gather information about the final product. The technology can minimise the amount of time needed to restart the facility and increase the stability of the manufacturing process by identifying aberrant signals and unforeseen circumstances in real time. Data is gathered and, with the aid of an operator or professional, is categorised as either faulty or good items. To prepare for training a deep learning model, the system analyses, normalises, and stores the pictures in a database. PLC receives the system's analysis of future events in order to regulate other devices. Almost any factory or factory-like setting might benefit from this technique.

II. SYSTEM DESIGN

A. SOFTWARE

TIA(TOTALINTEGRATEDAUTOMATION)

The Latest Release of the TIA Portal (Portal for Integrated Automation) Siemens' goal is to improve its engineering framework by adding features that are useful in practise across the whole process, from planning to construction to commissioning. Focus areas for TIA Portal V15.1 include the integration of Simatic S7-1500R/H controllers and Sinamics S210 drives, as well as Multiuser Engineering, software units, and OPC UA functions; these features allow for better digital modelling of integrated work processes.

For the purposes of simulation and virtual commissioning, the Simatic S7-1500 Controller is cloned in the TIA Portal using Simatic S7-PLCSIM Advanced. This digital twin is then integrated with mechatronic machine concept simulation software NX Mems Idea Designer (NX MCD) using the Simatic The device Simulator V1.0. Machine-level applications may be simulated and verified, allowing for the virtual validating of whole machines. This is made possible by the synchronisation of mechatronic controlling models, which can range from simple to complicated behavioural models. When controller and mechanical simulation models are combined, a digital replica of the actual application is created. This eliminates the need for physical prototypes and allows for the assessment and verification of simulated machines and optimisation procedures.To set up and code Siemens automation equipment,

you can use the TIA V15.0 software platform. The following languages are listed as being compatible with TIA V15.0 in the "Programming Guideline for S7-1200":

- Ladder diagrams (LADs) are a graphical language for depicting the contacts and coils in a relay logic circuit using icons.
- To visualise operates, operate blocks, and data kinds, there is the graphical language known as Function Block Diagram (FBD).
- A textual languages that employs propositions and terms to define a program's logic is called "Structured Text" (ST).
- Graphical language based on stages and transitions for describing a program's execution order is called Sequential Function Chart (SFC).
- A graphical language that employs mnemonics & operands to define a program's logic is called Statement List (STL).

B. HARDWARE

PLC (PROGRAMMABLE LOGIC CONTROLLER)

The abbreviation "PLC" refers to a device that can process digital and analogue input/output signals and carry out predetermined instructions to regulate mechanical components. For any control system requiring AI, this is the most important part. In this work, we present a unique method for integrating models developed using deep learning with PLCs, allowing for the two to interact and share control. Our objective is to develop and deploy a PLC edge model that makes use of in-built AI-based vision technologies. The edge PLC model may communicate with a cloud platform to share information and retrieve deep learning models that have already been trained, expanding its applicability to a wide range of goods and production facilities. We detail how our cutting-edge PLC model may be used to construct a product categorization model. The Siemens S7-1200 PLC is a small and flexible programmable logic controller utilised for a wide range of automation purposes, including but not limited to controlling, monitoring, and processing data.

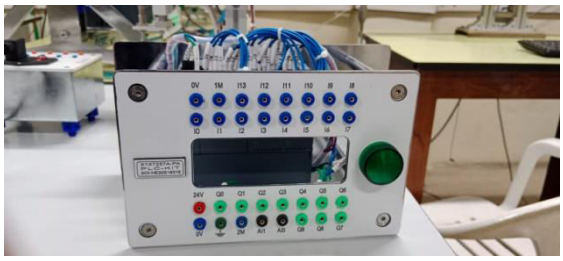

Fig: 1.1 Programmable logic controller

VFD (VARIABLE-FREQUENCY DRIVE)

An AC motor's speed and torque may be adjusted by adjusting the voltage as well as frequency of the input power, which is what variable-frequencydrivers (VFDs) do. Compared to traditional motor drives, variable frequency drives (VFDs) can reduce energy consumption, system inefficiency, noise, stress on the motor, and peak demand, among other benefits. VFDs may also regulate the starting and ramp-down from the motor at startup and shutdown.

There are three primary parts to a variable frequency drive: the AC motor, the main drive controller unit, and the drive/operator interface. An inverter, DC link, and rectifier bridge converter make up the primary drive controller. The rectifier bridges converter takes in alternating current and produces direct current. The DC link dampens the DC power source ripple and gives the inverter a solid input. The electricity from the DC source is changed into AC power with a frequency and voltage that can vary thanks to the inverter.

Approximately 75% of all drives in use across the world are variable frequency drives, and these devices find widespread usage in the control of fans, pumps, and compressors. Working idea, applications, configuration, construction schematics, interfaces with other equipment, and troubleshooting for variable frequency drives (VFDs) are all covered in this article.

Fig: 1.2 Variable frequency drive

CONVEYOR SYSTEM

Belt conveyor systems use a never-ending loop of conveying belts to move goods from one location to another. Conveyor belts have two or more spindles that create a closed loop when they revolve. A three-phase induction motor drives one of the pulleys to regulate the belt conveyor's speed and direction. The second pulley is an idler, which receives no power.

The conveyor system may be used to transport a wide variety of goods, including moulds, along a straight path or a curved path. The system can process either large quantities or single objects. A camera is installed on the belt conveyor to record footage of the items moving down the belts. After training, the GPU will recognise any flawed items in the photos. To

perform object classification and anomaly detection, the GPU employs a machine learning method.

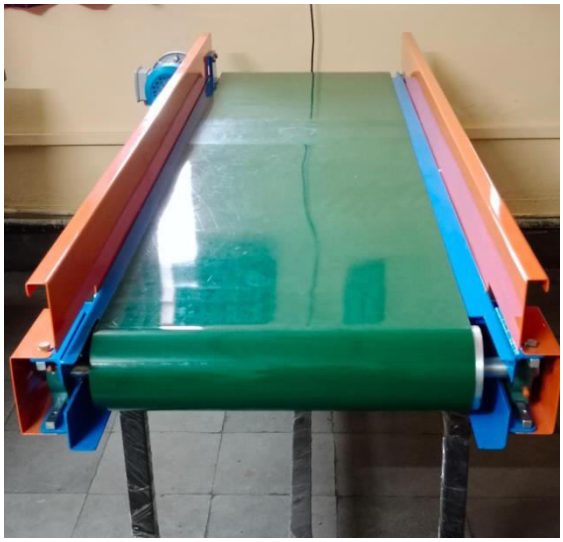

Fig:1.3 Conveyor system

NVIDIA JETSON NANO

Nvidia's Jetson Nano development system was introduced around the middle of March 2019. The creators of IoT devices are the target audience for this product. The board features a 1.43 GHz CPU and a Maxwell-generation GPU with 128 cores. The original version of the NVIDIA Jetson available to the general public. The official name of this device is NVIDIA Jetpack Nano A02. Miniaturised computing on the NVIDIA Jetson Nano. You'll need a computer and peripherals like a mouse, keyboard, and screen. The lack of on-board memory necessitates the use of an external storage device. For on-board data storage, the board is microSD-only. The OS and user data will be kept on this storage medium. A card with an microSD reader is likely required so that you can access and delete files from and to your computer. Nano NVIDIA graphics processing unit, microSD card, and an SD card reader. To operate the NVIDIA Jetson Nano gadget, you will often require some supplementary gear.

- GPU needs less memory than CPU.
- GPU’s Speed is more than CPU.
- GPU is suitable for parallel processing.
- GPU Emphasis on high throughput.

Fig:1.4 Nvidia jetson nano

III. DEFECT PRODUCT CLASSIFICATION MODELS

Pouring a hot metal into a mould and allowing it to cool and harden is called casting. Mould issues can cause casting items to be flawed or irregular, therefore they must be inspected before distribution to ensure they are up to snuff. Customer unhappiness and financial loss might result from casting defects.

The human eye may be used as a non-destructive inspection tool to determine if casting goods are defect-free or not using a process called visual inspection. However, visual inspection does have its limitations, such as the possibility of human mistake and the time it takes.

The purpose of this work is to develop a computer-vision-based automated inspection system. Convolutional neural networks (CNN), a type of deep learning model, are used to analyse photos of castings and determine whether or not they contain defects.

Dataset

In this work, we introduce a convolutional neural network (CNN) model tailored specifically to the problem of classifying damaged goods. We used 1,281,167 photos from 1000 classes (including both real and fake items) in the ImageNet, a 2012 dataset to train our model. Defect detection in casting goods is an example of a binary classification issue that our approach can solve. We tested our model on the casting process dataset [13]. The pixel dimensions of the 7348 colour photos in this collection are 300 on 300. The photographs were taken in a studio with precise lighting and staging.

Cast_def Cast_ok

Overview of the Dataset of Casting Products

This paragraph elaborates on how to go about gathering and organising data for an automatic learning endeavour. The objective is to determine if top-down photographs of mould products include defects or not. The camera manufacturer's EOS 1300D DSLR was used to capture these high-resolution photos. They already have quality labels such as "def_front" or "ok_front" applied to the photographs. To train and validate the model, you'll find the photos in the train folder, while to evaluate the model's performance, you'll find them in the test folder. In addition, the paragraph brings up the problem of disparities in classes in the input data, which might influence the model's precision. You can see the breakdown of flawed versus normal photos in the dataset in the scatter figure below. Even if the discrepancy isn't huge, it still has to be included in while developing and assessing the model.

1. **Data pre-processing**

The pixel values (which were originally between 0-255) must be scaled down to a range of 0-1 before the data can be used in the model. The rescale option of the KerasImageDataGenerator class makes this possible for both the training and testing datasets. In the data set generator, we used the parameter validation_split=0.2 to save 20% of the information for later verification. The pictures in the train/ and test/ folders are then loaded into the generators through the flow_from_directory() function. Some justifications for adding data and batch size are also provided.

Images should be 300x300 pixels in size, and color_mode='grayscale' should be used to convert them to a single-channel format. Class mapping should be set to either 0 for acceptable or 1 for defective.

There are two distinct classes, hence we must use class_mode='binary'

- 64-person minimum for batching

```
Define instances of ImageDataGenerator

Found 5307 images belonging to 2 classes.
Found 1326 images belonging to 2 classes.
Found 715 images belonging to 2 classes.
```

Fig: ImageDataGenerator

1. **Model building**

Convolutional neural networks (also known as CNNs) will be used in this research to analyse photographs of castings and determine whether they are defective or acceptable. Deep learning models such as convolutional neural networks (CNNs) are able to extract spatial

characteristics from clusters of nearby pixels in a picture. Since CNNs are able to learn from a wide variety of visual input, they find widespread usage in computer vision applications.

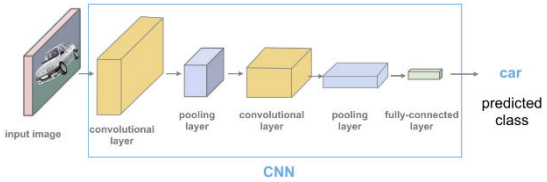

Fig: Layers of CNN

The above illustration depicts the many layers that make up a CNN, including the convolutional components (with activation), layers of pooling, and the last one, the fully-connected layer that generates class scores for an input picture. The convolutional component of a CNN serve as feature extractors that use the value of pixels of training pictures to infer the presence of certain shapes and colours.

Our model architecture will be based on that of the VGG models. The building block of the design consists of a series of convolutional layers with 3x3 filters, followed by a layer that maximises pooling. These cubes can have a filter size of 32, 64, 128, or 256.

Padding is used by the convolutional layers to maintain a constant height and breadth between the input and the output. Every layer until the last one uses the ReLU activation function. Since we are performing binary classification, we just need one node with the sigmoid activation function in the output layer. Adam as the optimizer (with a rate at which it learns of 0.001) or binary cross-entropy entropy as the loss function are used to train the model. For model training, precision is key.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 150, 150, 32)      320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 38, 38, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 19, 19, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 23104)             0
_________________________________________________________________
dense (Dense)                (None, 128)               2957440
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 2,976,385
Trainable params: 2,976,385
Non-trainable params: 0
```

Fig: Layers and parameters

1. **Model training and Evaluation.**

We use 20 training epochs and 83 steps each epoch to handle all of the network's picture batches as the model is trained. The ModelCheckpoint callback is used to save the model at the time of minimum val_loss. We'll keep this model for subsequent use in predicting test data.

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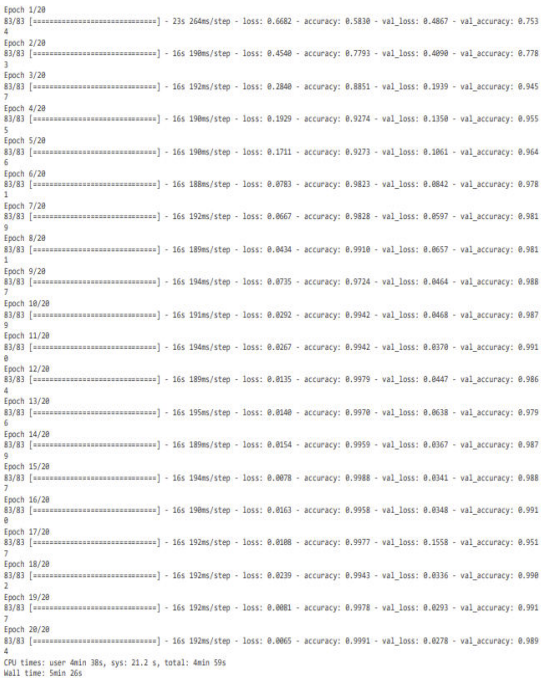

Fig: Training epoch process

1. **Using a model to classify new images**

New photos that were not used in the training of validation of the model are used in the test set. Each picture is given a probability value between 0 and 1 based on how strongly the model believes it belongs in the Defective class. To delineate the two groups, we use a threshold of 0.5. A Defective label is assigned to any item with a quality score of 0.5 or greater.

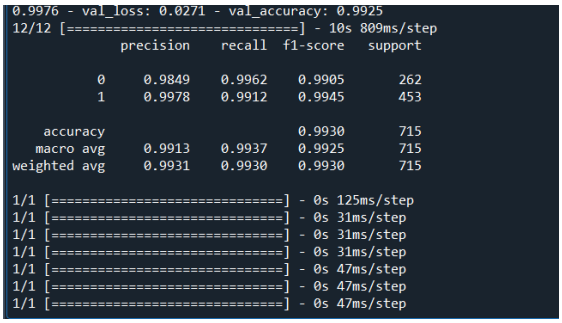

Fig: plots of deep learning

With a remarkable classification precision of 99.44% after training, the model incorrectly labels only 4% of 715 test photos. The model has excellent predictive abilities, with a recall of 99.78%, a high level of accuracy of 99.34%, and an F1-score for 99.56% for determining whether or not a picture contains a Defective casting.

The repercussions for the casting firm of incorrectly labelling defective castings as acceptable (false negatives) include lost clients and income. Waste, expense, and downtime may all be

amplified by the incorrect labelling of good castings as defective (also known as a "false positive"). Consequently, it is essential that both sorts of mistakes be reduced to the barest minimum.

When the cost of a false negative is high, recall might be a helpful statistic for gauging the model's efficacy. When the cost of false positives is high, precision is a helpful criterion with which to assess the model's performance. When both kinds of mistakes matter, an F1-score is a good statistic to use for judging the model's efficacy. Example of the a prediction and probability scores for test photos are displayed below.

IV. Expermental setup

In the training phase, the CNN network was trained on an outstanding performance. server computer running Ubuntu 18.04.6 LTS and equipped with an Intel Corporation processor Xeon E5/ Core i7 DMI2, 16 GB of RAM, and a GPU Quadro K600. The settings used for training are 0.1 learning rate, 8-epoch batches, and 20 epochs. How long it takes to train for one epoch on average, and how many parameters it has. We find that [8] requires the most time (168s) to train a single epoch. On the other side, one period of training takes just 65s. Figure 7 also shows the training curve used in the training procedure. After 33 iterations of training, all three networks show remarkably stable and excellent performance. These can be selected experimentally for use in the real world.

In the phase of deployment, we employ Jetson Pico [14], a tiny AI computer, to test the performance of the system. The brains of the Jetson Nano are a quad-core an ARM Cortex-A57 MPCore processor. These characteristics qualify it for Internet of Things use.

1. Expermental results

This work proves that the deep learning approach can be used to automate visual examination. After training the network, we test it on fresh data and use a confusion matrix to compare the network's actual and anticipated classifications. The number of properly and erroneously identified examples is displayed in a confusion matrix. Accurate categorizations can be found along the major diagonal that makes up the matrix. As the epoch count rises, the model's accuracy improves and its loss rate drops. Closeness between both validation and training curves indicates that the model has minimal overfitting and can accurately categorise test photos. These data from epoch 20 represent the greatest possible performance.

- 99.81% training accuracy
- 98.94%validation accuracy
- 0.76% training lass, and
- 2.78%validation loss.

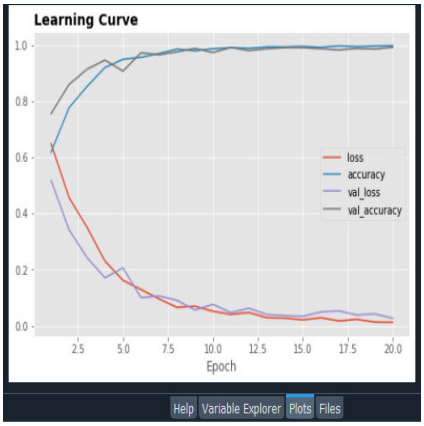

Fig: Training curves for deep learning network

Integrating this strategy into the manufacturing process can help trained inspectors better assess product quality. on page 4, table 4. After training the model on the server with test data, we deploy it to Jetson Nano following the steps outlined in Section 3.2. The camera feeds its data, at an area of 1280x720 pixels, into the Jetson Nano.

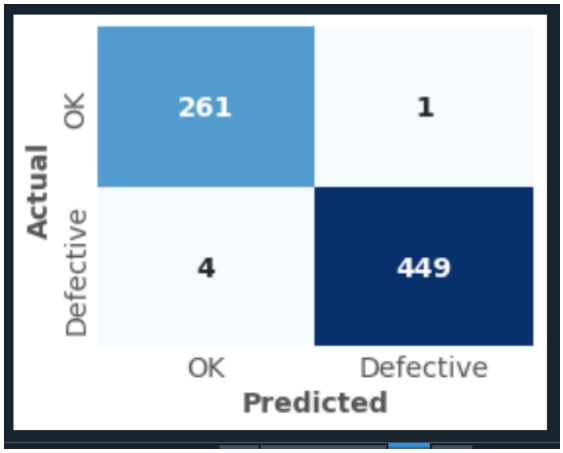

Fig: Confusion matrix

V. CONLUSION

This study introduces a unique system for smart industrial defect detection using deep learning methods. The system's three primary parts are a PLC module for controlling mechanical equipment, a cloud service, and an AI-embedded module (Jetson Nano). On a data set of casting products, we use knowledge transfer for tuning deep learning models. The Jetson Nano board is then used to install the simulator on the AI core module. The experimental outcomes prove show the system can perform input picture classification on an incorporated board with excellent accuracy and at real-time speeds. These findings show great promise and have broad implications. We want to test the strategy in the future using additional real-world data collected from a manufacturing setting.

FUTURE SCOPE

The development of new technologies, the needs of consumers, and the difficulties faced by businesses all have an impact on the potential reach of defect finding systems in the future. Here are a few potential areas for researchers to explore in the future:

Building models that are more flexible and generalizable so they may be used to a wide range of situations, failure modes, and products.

Use of computation at the edge, virtualization, and parallel processing to improve the effectiveness and capacity of defect recognition systems.

Discovering novel medical imaging, processing of food, aeronautical engineering, and other application areas for faulty product detection systems.

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