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Automatic Fabric Fault Detection Using Image Processing

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ABSTRACT:

This paper provides an overview of automatic fabric fault detection approaches that have been developed in recent years. Fabric fault detection is very important task in textile industry to ensure quality product. To help the textile industries we have developed an automated fabric fault detection system. This work proposes a method for classification of the fabric images into two categories : Defective and Non-Defective. In this proposed work fabric dataset is collected from the AITEX website and this dataset consist of 140 non defective fabric images and 105 defective images. Convolution Neural Network (CNN) based on Transfer Learning Technique using VGG16 model is employed for classification. We have also used fine-tuning and data-augmentation techniques in terms of enhancing classification accuracy.

Keywords: *Fabric Defect Detection, Neural Network, Image Processing, Tensorflow .*

INTRODUCTION

The most important element in clothing is the fabric. The fabric is in the form of a dress. Fabric quality is essential as it contributes to a pleasant feeling while wearing. The use of high quality fabric makes the fabric last longer and easier to care for.

DESCRIPTION:

Automatic flaw identification is difficult due to the wide variety of shapes and types of fabric faults. An efficient error detection system helps manufacturers enhance the quality of their operations and products. Textile waste is minimized, and revenues are raised as a result of cost and resource savings made throughout the manufacturing process. Several research on automatic fall detection systems based on image processing and machine learning techniques have recently been published. These techniques vary depending on the manufacturing processes and the kinds of faults. Researchers were also able to create a real-time mistake detection system throughout the weaving process.

Automatic inspection of colored cloth is a major research subject in manufacturing and quality control at this stage in the production process of more than two decades. Its aim is to identify flaws on the stained fabric's surface and paint them away, which was formerly done by workers but resulted in human error, high labor costs, and long processes. As a result, automated visibility in the textile industry enhances the monitoring of such controls and increases the accuracy of quality control detection. The CNN-based image processing technique is utilized to overcome these obstacles. The insertion pattern is a delicate fabric, and any roughness or rips are deemed faults and documented. The following are some of the most frequent blunders:

- Yarn defects
- Weaving defects

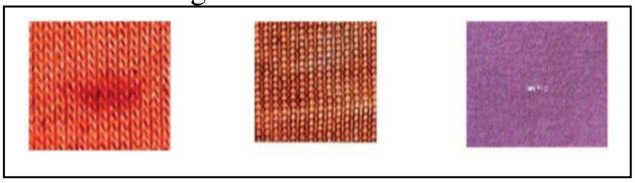

Fig1: Yarn and Weaving Defects

LITERATURE SURVEY:

Past research has proposed several methods to fabric fault detection.

[1] A. Kumar and G. K. H. Ache

developed various methods for automated inspection of completed products using Gabor wavelet highlights in 2002. Another method for recognizing a class of deformities in material networks using guided imperfection localization is presented. The use of a multichannel separation scheme for unaided online examination is investigated. Another information multiplexing strategy is suggested to multiplex the data from the different channels. Different aspects of the balance between execution and computational load are investigated. Over the previously suggested methods, this strategy builds up a large computational reserve fund, resulting in superior imperfection location. The final acceptance of visual examination frameworks is also based on practical considerations.

[2] IN 2008 R. Furferi and L. Governi

Developed a system for recognizing and classifying defects on material crude textures in 2008. The apparatus (programming + equipment) is simply linked to a well-designed examination hardware machine (weaving room checking framework), and the evaluation is done online. The created apparatus performs (1) crude texture picture acquisition, (2) basic boundary extraction from the obtained pictures, (3) a fake neural organization (ANN)-based methodology ready to identify and arrange the most frequently occurring kinds of deformities on the crude texture, and (4) a standard picture handling calculation that allows the estimation of them.

[3] In 2018 W. K. Wong and J. L. Jiang

published a book called Applications of Computer Vision in Fashion and Textiles, which provides a thorough and comprehensive discussion of three key areas that are benefiting from advancements in computer vision technology, including material imperfection detection and quality control, style recognition and 3D displaying, and 2D and 3D human body demonstrating for further development. It covers the fundamentals of PC vision strategies for design and material applications, as well as PC vision techniques for material quality control, including sections on wavelet transformations, Gibor channels, Fourier transformations, and neural organization processes. The last sections include recognition, demonstration, recovery advances, and advanced human form showing methods.

[4] In the year 2019, W. Ouyang, B. Xu, and J.

By combining the strategies of image pre-handling, texture theme assurance, up-and-coming deformity map age, and convolutional neural organizations, Hou and X. Yuan developed a deep learning calculation for an on-loom texture imperfection evaluation framework (CNNs). With the help of a CNN and a new pairwise-potential actuation layer, high precision imperfection division on textures with puzzling components and an unbalanced dataset was achieved.

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PROPOSED METHOD:

SYSTEM ARCHITECTURE

This architecture diagram illustrates how the system is built and is the basic construction of the software method. Creations of such structures and documentation of these structures is the main responsible of software architecture.

CNN is a type of neural architecture that is widely used in the field of computer vision. It has proven to be very effective because it has been transformed into a go-to method for most image information. At least one convolutional layer, known as the main layer, is present in CNNs and is responsible for image extraction. CNNs capture highlights from data using extraction channels and analyze the contribution of a few bits at a time before forwarding the result to the next layer. The component map is created by the convection layer using convection channels. The dimensions are reduced with the help of the assembly layer, which reduces the manufacturing time and prevents over-fitting. The most commonly used pooling layer is the pooling cap, which takes the highest value in the pooling window.

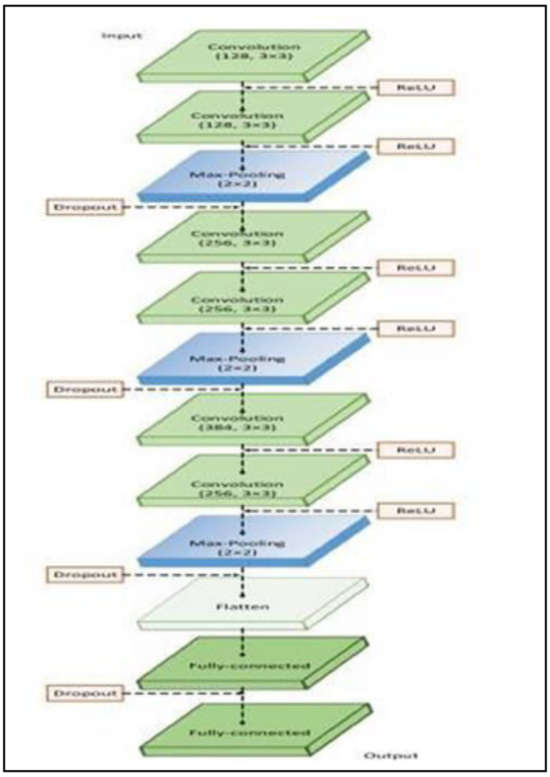


Fig.2: System Architecture

DATA FLOW DIAGRAM

Data flow diagram also referred as bubble graph. This diagram is useful for representing the system for all degree of constructions. The figure is differentiated into parts which show maximizing data path & practical aspect.

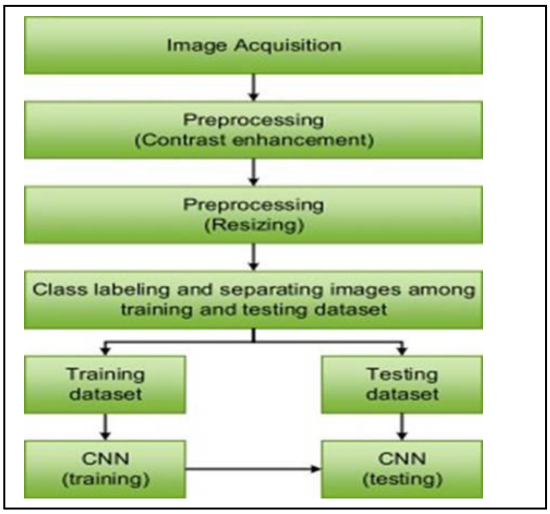


Fig 3: Data Flow Diagram

METHODOLOGY

DATASET- AITEX FABRIC IMAGE DATABASE

The material texture information base comprises of 245 pictures of 7 distinct textures. There are 140 deformity free pictures, 20 for each sort of texture. With various kinds of imperfections, there are 105 pictures. Pictures have a size of 4096×256 pixels.

Defective images have been denominated as follows:

nnnn_ddd_ff.png, where nnnn is the image number, ddd is the defect code, and ff is the fabric code.

Defect free images have been denominated as follows: nnnn_000_ff.png, where defect code has been replaced by 0000 code. Defect Codes used in the database:

Broken end	2	Broken yarn	6
Broken pick	10	Weft curling	16
Fuzzyball	19	Cut selvage	22
Crease	23	Warp ball	25
Knots	27	Contamination	29
Nep	30	Weft crack	36

Fig 4: Collecting Data Set

CONVOLUTION NEURAL NETWORK:

The convulsive sensory system is a top to bottom learning model used to comprehend issues, for example, recognizing and grouping complex models in various informational indexes. The model comprises of four distinct layers one on top of the other: separate wrapping layer, most extreme pooling, completely fortified and yield layer. The uniqueness of the plan lies in its adaptability in fitting dependent on the task results.

A wide assortment of CNN models are accessible, including AlexNet, VGG, GoogleNet, Resnet and others. These models change inside and out just as their plans, nonlinear sufficiency and number of units.
There are numerous modifiable factors, for example, dropout rate and learning rate that can be utilized in complex preparing to tackle portrayal and model acknowledgment issues.

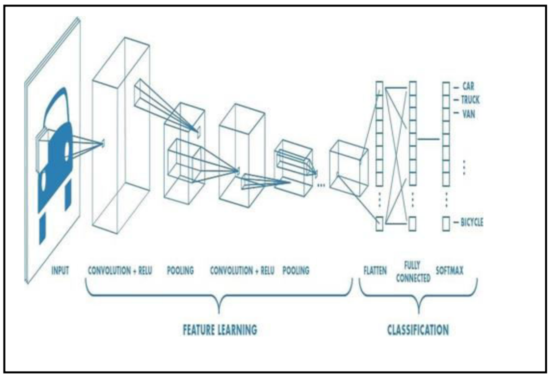


Fig 5: Multi-layer Conventional Neural Network. Torsion layer.

FUNCTION OF ACTIVATION

A Sigmoid capacity is a numerical capacity with a particular "S"- formed bend or sigmoid bend that differs somewhere in the range of 0 and 1. It is utilized in models where the likelihood should be anticipated as a yield.

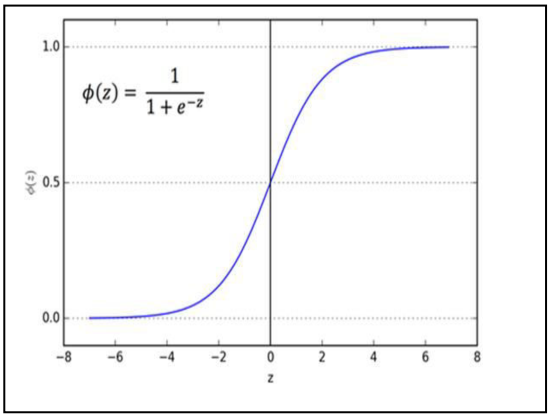


Fig 6: sigmoid Curve

Since the sigmoidal function is differential, we can determine the slope of the curve at any two locations.
Adequate passive input on the sigmoid activation function causes the neural network to shut down during training.

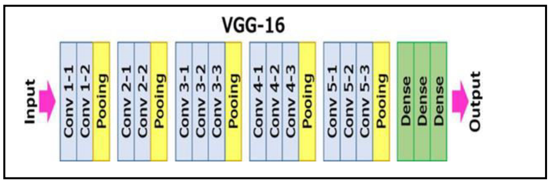


Fig 7: VGG16 architecture

Section to the Cov1 layer is a decent size with a 224 x 224 RGB picture. The picture is handled by a pile of curved (temporary) layers with a tiny gathering field: 33 (littlest size to catch left/right, top/base and focus ideas). It additionally utilizes 11 convolution channels in one of the settings, which can be considered as straight regulation of information channels (later non-direct). The change step is set to 1 pixel and the spatial cushioning for the progress. Layer input is set to 1 pixel for 33 changes. Layers, so the spatial goal is saved after convolution. Five layers for most extreme get together, which follows some piece of the progress. Layers, make a spatial gathering (not all progress layers are trailed by a most extreme gathering). The subsequent advance is max pooling on a 22 pixel outline.

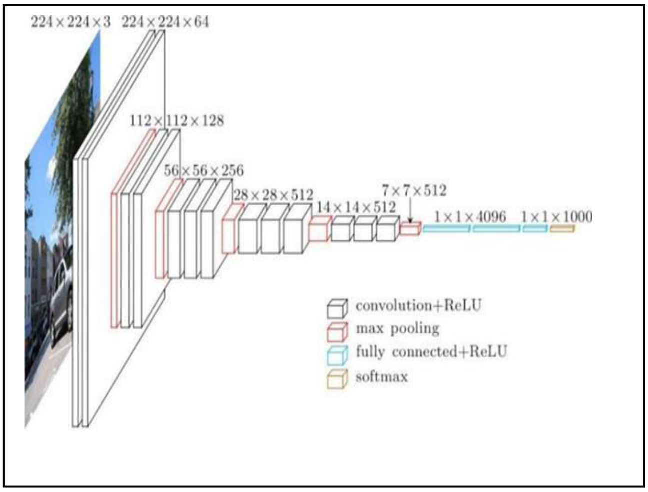


Figure 8: VGG 16 Architecture

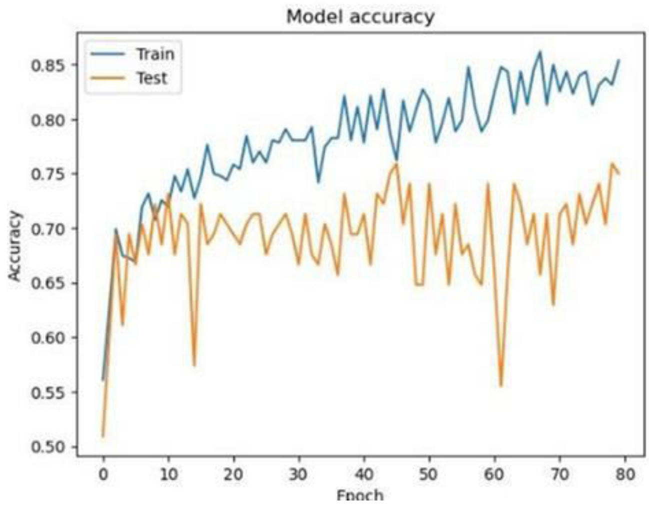
Following the pile of convection layers (which have various profundities in various plans), three completely associated layers (FC) are added: the initial two have 4,096 channels each, and the third layer keeps an ILSVRC rating of 1,000 bearings and along these lines 1,000 channels (each). Season). The smooth-most extreme layer is the last layer. In all organizations, the sythesis of the comparing layers is actually something very similar.

Non Linear Correction (ReLU) is available in totally covered layers. The ILSVRC doesn't further develop execution on the dataset yet ought to likewise feature the way that none of the organizations (aside from one) utilize the Local Response Match (LRN) which builds memory utilization and calculation time.

The proposed method has following advantages.

Advantages:

- It may be used to models incorporating multiple light components without any modification, allowing for the identification of various faults in various fabrics.
- This method allows to identify different defects in different garments.



Results:

The consequences of addressed procedure center around:

- The essential undertaking is to characterize the info picture as a deficient or faultless configuration picture.

CONCLUSION

This technique makes it easier to spot defects in the image. Vision monitoring is a time consuming task that requires watching, paying attention and trying to correctly identify failures. This method is more accurate and effective in detecting tissue abnormalities. With the help of advanced management system models we can identify and repair real world damage in the textile sector.

Fig 9: Model Training and testing accuracy (%)

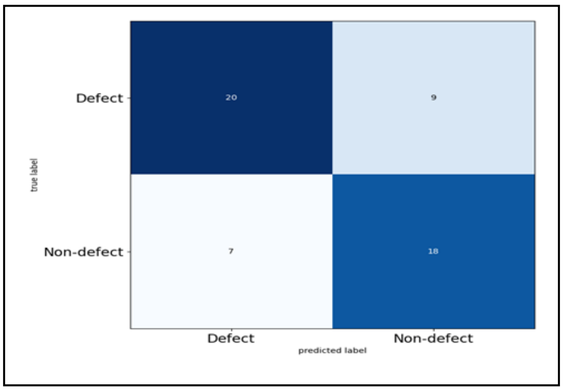
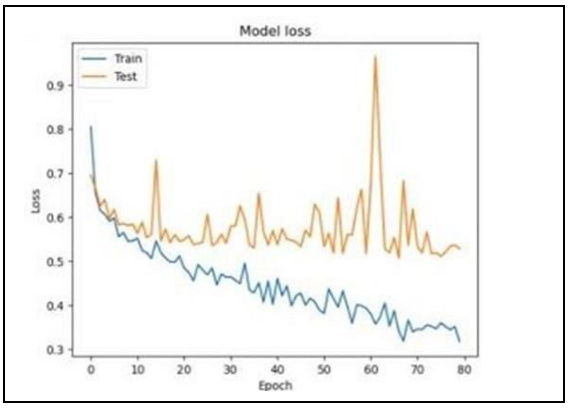


Fig 10: Confusion matrix for validation



Future Enhancement:

- ✓ The utilization off some other capacity rather than Soft max enactment capacity can upgrade the exhibition off the CNN making it perfect for ordering numerous Defection.
- ✓ Counter estimating the irregularities experienced working with constant dataset.
- ✓ To construct a Web/Internet off Things (IOT) empowered on going ailment checking framework.

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