"EMPOWERING INDIA THROUGH DIGITAL TRANSFORMATION : A SUSTAINABLE APPROACH"

Volume - I

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Digital Transformation and Applications of Artificial Intelligence in Handloom Industry

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Abstract

Every nation treasures its handloom heritage, and in India, the handloom industry safeguards cultural traditions, sustains millions of artisans, and preserves ancient weaving techniques. To protect this legacy, a critical need arises to distinguish genuine handloom products, exemplified by the renowned "gamucha" from India's northeast, from counterfeit power loom imitations. Our study's objective is to create an AI tool for effortless detection of authentic handloom items amidst a sea of fakes. Six deep learning architectures—VGG16, VGG19, ResNet50, InceptionV3, InceptionResNetV2, and DenseNet201—were trained on annotated image repositories of handloom and power loom towels (17,484 images in total, with 14,020 for training and 3464 for validation).

A novel deep learning model was also proposed. Despite respectable training accuracies, the pre-trained models exhibited lower performance on the validation dataset compared to our novel model. The proposed model outperformed pre-trained models, demonstrating superior validation accuracy, lower validation loss, computational efficiency, and adaptability to the specific classification problem.

Notably, the existing models showed challenges in generalizing to unseen data and raised concerns about practical deployment due to computational expenses. This study pioneers a computer-assisted approach for automated differentiation between authentic handwoven "gamucha"s and counterfeit power loom imitations—a groundbreaking recognition method. The methodology presented not only holds scalability potential and opportunities for accuracy improvement but also suggests broader applications across diverse fabric products.

Keywords : *Textile loom type, Handloom fabric, Power loom fabric, automated identification, Artificialintelligence, Deep learning.*

Introduction

The pride and protection of handloom heritage are sentiments shared by many countries across the world. Handloom traditions represent an essential part of a nation's cultural identity and history, and they are revered for their artistic craftsmanship and time-honored techniques. In the textile industry, India plays an important role where it contributes to 15% of the total Industrial production and nearly 30% of the total exports. In fact, it is the second largest employment generator after agriculture. The textile sector in India encompasses modern textile mills, independent powerlooms, handlooms, and garments. Handloom holds significant economic importance, particularly for traditional products like the renowned "*gamucha*" towel from Assam, India, valued not only for its utility but also cultural symbolism. It is a white rectangular piece of cotton hand woven cloth with primarily a red (in addition to red, other colors are also used) border on two/three sides (longer side) and red woven motifs on the one/two sides (shorter sides).

Despite its cultural significance, the handloom industry faces a severe crisis, exacerbated by competition from powerlooms selling products deceptively as handloom items. The 2019–2020 Indian handloom census revealed Assam to have the highest number of weavers' families, with 10.9 lakh (38.6%) households, predomi- nantly in rural areas. Unfortunately, the crisis has disproportionately affected female weavers, constituting nearly 80% of the handloom workforce in the state.

Efforts by the State's Handloom and Textile Directorate, including raids on powerloom products, have been hampered by the lack of valid laboratory certificates to support complaints, leading to the release of confiscated items back to retailers or wholesalers.

Addressing this issue is crucial to preserving the handloom heritage and supporting the livelihoods of the weaver community.

Mechanism of Handloom "*gamucha*" Fabric Production

Fabric production begins with yarn, crafted from various fibres, either natural or man-made. Although the "*gamucha*" is woven in various yarns, like silk, wool, etc., the cotton thread or yarn is used most commonly. After passing through stages, yarn is derived from these fibres, which must possess specific properties to qualify as textile fibres. Fabric, typically woven, requires two thread series: warp (longitudinal) and weft (transverse). Weaving involves interlacing these series in a loom. However, before weaving, the longitudinal warp threads undergo preparatory processes. Yarn is often in hank form, unsuitable for warping. Preparatory weaving processes include sizing, winding, warping, beaming, looming, and finishing. Sizing involves coating the yarn for strength and uniformity. Winding transfers yarn from hank to bobbin. Warping involves preparing the warp sheet, fol- lowed by denting to draw threads through reed dents. Beaming transfers the warp sheet to the warp beam. Thefinal steps include heald (a device used in weaving looms to control the movement of warp yarns) knitting and looming, where the shuttle passes through the warp-shed, completing the weaving process. This comprehensive process ensures the creation of high-quality handloom "*gamucha*" fabric production.

Powerloom "*gamucha*" and Challenges thereof

The production of high-quality handloom "*gamucha*" demands significant skill and time from weavers, resulting in a meticulous process. In contrast, powerloom counterparts can be mass-produced at a lower cost due to the use of cheaper yarns. The challenge arises due to the subtle differences between the two types, making it difficult for both non-experts and even experts to distinguish them without scientific support.

Experts rely on manual observations of features. Few common differences observed are:

These observations span different sections of the "*gamucha,*" including selvedge and short edges, inner body, and motifs. Images from all these sections contribute to the identification of the loom type. Figure 3 visually outlines features crucial for expert manual identification. All these images have been captured using the iPhone 12 smartphone in 4x zoom and in natural light. Further,handloom "*gamucha*" and powerloom "*gamucha*" are presented for comparison. Placing similar sections of the cloth one above the other underscores the challenge of distinguishing between them, emphasizing the need for a systematic approach, such as the proposed automated recognition system, to address this complexity.

Artificial Intelligence (AI) in the Textile Industry

Within the landscape of the Fourth Industrial Revolution (IR4.0), AI emerges as a cornerstone in the textile industry, significantly enhancing the quality of textiles. Its pivotal role lies in its capacity to adeptly identify defects, thereby contributing to the overall improvement of textile standards. It is gaining prominence, particularly in the areas of loom type detection and fraud prevention. AI-driven technologies, such as computer vision, play a pivotal role in accurately identifying various loom types, streamlining manufacturing processes, and ensuring quality control. Additionally, AI's advanced analytics capabilities are instrumental in detecting fraudulent claims within the industry, mitigating risks and ensuring transparency. By harnessing AI for loom identification and fraud prevention, the textile sector not only enhances operational efficiency but also establishes a foundation for trust and integrity within the supply chain.

Rationale of the Study

The significance of this study lies in its potential to assist handloom experts in their identification process, addressing a critical need in the industry. By incorporating AI technologies, specifically deep learning models and transfer learning architectures, we aim to classify handloom "*gamucha*"s from power loom counterparts with cotton yarn type. Our study introduces a novel deep learning model for automated loom type identification, filling a gap in existing literature and representing a pioneering effort in this domain. By addressing these aspects, the research endeavors to contribute not only to the technological advancement of the textile industry but also to the preservation and sustainability of traditional handloom practices in the face of contemporary challenges.

The contribution of this study can be bulleted as follows:

Prior Art

The application of AI in the domain of textile fabrics has alluded attention, although being a crucial one. It is observed that the first phase of works was initiated in 2005, where porosity calculation was done on 30 microscopic images of plain woven cotton fabrics. To assess the textile porosity by the application of the image analysis techniques, it was revealed by the authors that light transparency of the looser fabrics is higher than that of the tighter ones because of the more significant pore dimensions. The subsequent study was reported in 2010, where the authors employed Discrete wavelet transform, and the first-order statistical features, such as mean and standard deviation, are obtained and stored in a library. The obtained value is compared with the reference image value for determining any kind of defects on the fabric. Here, the study aimed to identify defects in a handloom silk fabric using image analysis techniques.

In 2011, a study on fabric texture analysis was done using the computer vision technique. The other study presented an application of machine learning to distinguish between different materials such as carpet, flooring vinyl, tiles, sponge, wood, and polyvinyl-chloride (P.V.C.) woven mesh based on their surface texture. Several machine learning algorithms, such as Naive Bayes, decision trees, and naive Bayes trees, have been trained to distinguish textures sensed by a biologically inspired artificial finger.

The subsequent development was reported in 2014, where the authors developed a novel structure detection method based on Radon transform using high-resolution images of fabric yarn patterns. Applied on three kinds of yarn-dyed cotton of 24 samples of microscopic images, it was shown that the edge-based projection method performs better than the gray projection method, especially when there is long hairiness on the fabric surface for identification of warp and weft. Using texture feature for textile image classification was further provided in 2015, using 450 different textured images of different cloth material with variant design. The authors have used feature extraction methods G.L.C.M., Local binary pattern, and moment invariant (MI). Then feature reduction is performed using P.C.A., followed by classification using SVM. The accuracy achieved is 74.15%.

In 2016, Jing et al. worked on fabric defect detection on the T.I.L.D.A. database using Gabor filters for feature extraction, followed by feature reduction kernel P.C.A. Euclidean normal and OTSU is used for similarity matrix calculation. The sensitivity, specificity, and detection success rate are measured and reported to be 90% to 96%. Specificity is in the range above 96%, and the detection success rate is above 93% for different defect types. 2017 saw another novel biologically-inspired method to invariantly recognize the fabric weave pattern (fabric texture) and yarn color from the color image input. The authors proposed a model in which the fabric weave pattern descriptor is based on the H.M.A.X. model for computer vision inspired by the hierarchy in the visual cortex. The color descriptor is based on the opponent color channel inspired by the classical opponent color theory of human vision. The classification stage is composed of a multi-layer (deep) extreme learning machine. In 2018, Huang et al. performed a study on textile grading of fleece based on pilling assessment using image processing and machine learning methods. Three hundred twenty representative samples were collected from

fabrics and classified as grade 2, 3, 4, or 5—each grade comprised 80 samples. The obtained grayscale images were filtered using two methods: the DFT method combined with Gaussian filtering was used to smooth the grayscale images. ANN and SVM are used for classification. Classification accuracies of the ANN and SVM were 96.6% and 95.3%, respectively, and the overall accuracies of the Daubechies wavelet were 96.3% and 90.9%, respectively. Again, another work provided a literature review on the application of data mining and machinelearning in the textile industry.

In a 2023 study by Bora et al., a methodology employing a Machine Learning (ML) classifier and utilizing a database of 7200 images from handloom and powerloom types achieved a notable 97.83% accuracy in auto- mated loom recognition. The approach involved extracting texture features, employing significant ones based on a t-test, and training using all possible feature combinations. Precision rates were 97% (handloom) and 98% (powerloom), with recall rates of 98% (handloom) and 97% (powerloom). Notably, the study focused only on digital camera images and lacked validation results.

Methodology

Materials Used

For our study, we obtained high-resolution images of segments from "*gamucha*"s using a predetermined methodology. Specifically, we captured images from 200 pieces, with an equal distribution of 100 from handloom and 100 from power loom classes. Two different Smartphone models (iPhone 12 and Xiaomi 11i) were used to address source variation. External factors such as illumination (pictures were taken without flash), focus (we manually observed focus by tapping on the phone), and distortion (we tapped on the phone along a bent line, if present, and held until the line straightened automatically) were taken into account during image capture, maintaining a distance of 5–10 cm from the fabric. By following a systematic dataset curation flow, bulleted below and depicted we ensured the representation of various features of "*gamucha*"s in our dataset, preparing it for training and validation in the development of a smartphone-based app.

Methods (Deep Learning Models)

With the emergence of deep learning techniques, textile engineering has adopted deep networks for providing solutions to classification-related problems. These include classification based on fabric weaving patterns, yarn colors, fabric defects, etc.. We investigated the performance of six deep learning architectures, which includeVGG16, VGG19, ResNet50, InceptionV3, InceptionResNetV2, and DenseNet201. Each model is trained with annotated image repositories of handloom and powerloom "*gamuchas*". Consequently, the features inherent to the fabric structures are 'learned', which helps to distinguish between unseen handloom and powerloom "*gamucha*" images. Deep learning obviates the requirement for independent feature extraction by autonomously learning and discerning relevant features directly from raw data. This inherent capability streamlines the process, enhancing adaptability to diverse datasets and eliminating the need for manual feature engineering.

six deep learning models are employed to perform classification with the objective of differentiating handloom "*gamucha*"s from powerloom "*gamucha*"s. The technical and architectural description of each model is provided below:

VGG Neural Networks

V.G.G. is a convolutional neural network (CNN) architecture which addresses the important aspect of depth in deep networks and uses small convolutional filters, allowing the model to have a large number of weight layers. Our work considers the two most successful deep CNNs proposed by VGG-VD, namely VGG16 and VGG19 with 16 and 19 weight layers, respectively. Both these networks use a stack of 3 × 3 kernel-sized filters with stride 1, thus presenting a small receptive field. These are further followed by multiple non-linearity layers. This contributes to increasing the network's depth and helps learn more complex features with discriminative decision functions. This architecture proved to be a tremendous breakthrough in image classification with an achievement of 92.7% top-5 test accuracy in the ImageNet dataset. Liu et al. experimented with VGG16 and its variants and concluded their effectiveness in detecting complicated texture fabrics. Considering this analysis in the textile domain, we adopted VGG16 and VGG19 for our classification problem.

Residual Neural Network (ResNet)

In, the concept of residual networks was introduced, emphasizing the vanishing gradient problem in deep networks that causes learning to be negligible at the initial layers in the back propagation step. The deep ResNet configuration overcomes this issue by employing a deep residual learning module via additive identity trans- formations. ResNet is the winner of the classification task in the ILSVRC-2015 competition and has been used as a basic structure in many fabric recognition and classification applications. Inspired by the performance of ResNet in these domains, we experimented with ResNet50. It is a variant of the ResNet model, which has 48 convolution layers along with 1 max-pooling and 1 average-pooling layer.

Inception

Inception networks were introduced by Google Net, which are proved to be more computationally efficient, both in terms of the number of parameters generated by the network and the economic cost incurred (memory and other resources). Inception v3 is the third version of the series with additional factorization convolutions, aiming to reduce the number of parameters while maintaining network efficiency. In addition to this, several othertechniques for optimizing the network have been suggested to loosen the constraints for more straightforward model adaptation. These techniques include regularization, dimension reduction, and parallelized computations. The model comprises different sized filters at the same layer, which helps obtain more exhaustive information related to variable-sized patterns. Moreover, Inception v3 is widely adopted in image classification tasks and is proved to achieve 78.1% accuracy with Image Net Dataset and top-5 accuracy about 93.9%.

Results

Implementation and comparative analysis of different deep learning architectures

This subsection presents experimental results and comparative analysis to conclude with the best model among the selected classification networks—this aids in obtaining an efficient solution for our stated problem.

Implementing the VGG16 architecture the accuracy arrived was around 50% to 56%. The training curve Implementing the first modification, the model reached a maximum training accuracy of 99.94% and a validation accuracy of 91.99%, as revealed in the training curve. Next, implementing the second modification, the model reached a training accuracy of 95% and a validation accuracy of 90% after 15 epochs.

Finally, implementing the third modification, the model achieved a training accuracy of 98.47%, and a validation accuracy of 94.39%, after 43 epochs. This model was then tested on 25 unknown images of each type each, which were augmented (horizontal flip, vertical flip and mirroring the horizontal flip, vertical flip) to 100 images each type. The accuracy obtained was 98.0%, revealed in the training curve.

It was seen that some powerllom "*gamucha*" were wrongly identified as handloom. These images were identified and checked and were found to be blurry, indicating that the images have to be well focused before running the model.

Comprehensive Overview of Model Characteristics

In the context of deep learning models, "space occupancy," "number of parameters," and "associated depth" refer to different aspects of a model's architecture and characteristics:

Space Occupancy: Space occupancy typically refers to the memory or storage requirements of a deep learning model. It represents the amount of memory needed to store the model's parameters and other information required for inference or training. This is usually measured in terms of megabytes (MB) or gigabytes (GB) of memory. A model with high space occupancy requires more memory for its operation.

Number of Parameters: The number of parameters in a deep learning model refers to the total count of learn-able weights and biases that the model uses to make predictions or classifications. In neural networks, these parameters are typically associated with the connections between neurons in different layers. More parameters often allow a model to capture more complex patterns in data, but they also increase the computational and memory requirements.

Associated Depth: The depth of a deep learning model refers to the number of layers it has. Deeper modelshave more layers, and each layer typically performs a specific transformation of the input data. Deeper modelscan capture more intricate hierarchical features in the data, but they may also be more challenging to train and require more computational resources.

Comparative assessment of various deep learning models for classification of loom type. process but also offers a user-friendly mobile application for seamless deployment, facilitating wider adoption and practical implementation. Moreover, the study's contributions extend beyond technological advancements, addressing broader societaland economic aspects. By safeguarding the integrity of handloom products and supporting the livelihoods of weavers, the research aligns with the goals of preserving cultural heritage and promoting sustainable practices in the textile industry. Additionally, the integration of AI technologies fosters transparency and trust within the supply chain, mitigating fraudulent practices and ensuring consumer confidence.

Conclusion

In essence, the study represents a holistic approach towards addressing contemporary challenges faced by the handloom industry, encompassing technological innovation, socio-economic empowerment, and cultural preservation. By embracing AI-driven solutions and fostering collaboration between traditional craftsmanship and modern technology, the research paves the way for a sustainable future for handloom traditions in the digital age.

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