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Deep Learning Technique For DetectionOf Fake Cloth

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Abstract

Manufacturing and distribution of fake clothing material which can be inferred to be criminal in nature has become a rapidly growing online shopping concern. It can be seen as a way of disguising false information as legitimate. Indeed, many fashion industries face challenging times to meet market sales and expected profits once fake clothing products are sold on street corners. The consequences of clothing counterfeiting also range from huge losses to buyers and sellers of original products to health hazards, loss of image, and slow growth. More so, while IT has been beneficial, the introduction of IT has also provided a global platform for elusive counterfeiters and traders. The need for efficient/effective techniques for identifying or differentiating original clothing materials from fake ones is consequently on a geometric rise. This study developed and evaluated a fake cloth detection model using Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Autoencoder using Python programming. The goal was to improve the capacity for discerning genuine and fake fabric items through image analysis. The dataset acquired from Kaggle was used for the training, testing, and validation phases in the ratio of 70:20:10 respectively. The processes include resizing the images to a uniform size, converting them to grayscale or applying colour normalization, and removing any irrelevant information. Data augmentation methods were applied to enhance the dataset's diversity. Results obtained from the implementation of the model show that the CNN model achieved perfect precision and accuracy, indicating that it performed well on the dataset. The RNN model achieved 97% precision while the Autoencoder model had a lower precision and accuracy compared to the CNN and RNN models. It correctly identified 63% of the positive instances, but its overall accuracy was 56%, indicating that it struggled with the correct classification. These results also highlight the importance of selecting appropriate algorithms that align with the specific task requirements, especially as it found the autoencoder may excel in unsupervised learning scenarios, but its limitations become apparent in supervised classification tasks like fake cloth detection.

Keywords: *Fake clothing, cloth quality authentication, neural network, autoencoder, counterfeiting detection*

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I. Introduction

The advent of Information Technology (IT) has offered tremendous benefits to virtually all aspects of human life. Among these benefits are improved efficiency, automation, and expediency with reduced costs. Information Technology is noted to have delivered several innovations in governance, human resource management, education, businesses, weather forecasting, health, communication, decision making and shopping [1-11]. Before now, online sellers required the technical knowledge of system design and programming to develop and operate the shopping platform. However, modern-day IT tools present sellers the opportunity to seamlessly set up online stores on social media and e-commerce platforms as well as share product profiles and images. Considerable reduction in the development, operation and management costs of online shops is now being experienced due to the benefits of IT. Fashion is presented in various ways to the world by different people and remains one of the biggest industries in the world. People's dress and makeup presentcultural uniqueness and peculiarities and fashion is primarily communicated through sight and has attracted much interest from researchers in the field of computing in recent times. Researchhas been reported on fashion analysis, which is a complex problem that requires practical solutionsforclothing product classification and detection, image retrieval, and overlay augmented reality, among others.

Determining the quality levelof clothing is known to be among the first technological challenges for fashion analysis. However, most of the fashion analysis tasks centred on identifying the locations of clothing items viaseveraltechniques that exhibit high levels of accuracy [12]. However, as against the situations in other sectors, it is easier to imitate or fake fashion products. While imitation can be seen as a form of flattery, fashion counterfeiting causes significant damage to brand reputation and income. Counterfeit products are being sold in marketplaces and online as replicatesof the original goods with buyers unable to distinguish them from the original[13].According to [14], fashion products that are often counterfeited include clothing, jewellery, watches, footwear, and leather goods. It was also reported that several millions of counterfeited pairs of shoes (such as Adidas, Puma Sports, and Adidas) as well as toys and textiles are being seized at international airports with a total estimated value of over 500 million Euros. Similarly, the International Anti-Counterfeiting Coalition had seized fake apparel, foot wear, and handbags that were worth several millions of dollars across the US, China and some other state borders[15-16].

The sale of fake products threatens the ability of many fashion industries to meet market sales and expected profits. It can also lead to huge losses to buyers and sellers of original products, health hazards, loss of reputation and patronage, and slow growth. Though IT has brought several other advantages, its implementation has also created a platform for elusive counterfeiters and ill-intentioned traders. Research has shown that approximately one-fifth (20 per cent) of all Instagram fashion-related posts showcase counterfeit items. Counterfeiting can be exhibited through fake logos, false labelling and deceptive packaging all with the motive of deceiving and misleading consumers.Deep learning techniques are being tipped as valuable methods for distinguishing between authentic and counterfeit products.Deep learning is a subset of machine learning and it is noted for exceptional accuracy when trained on large datasets. One of the most pronounced deep learning techniques is the Convolutional Neural Network (CNN) which has been established for excellent object recognition compared to other deep learning algorithms. CNN uses its classification structure to categorize images into labelled classes. It is also noted for high performances in spatial data analysis, computer vision, natural language processing, and signal processing, among others[13].

Several techniques for the detection of the quality levels of clothing materials are reported in [12, 17-20]. The limitations of these techniques include complicated pattern and textures-induced failure, low dataset, low detection accuracy, wrongly labelled data, and computational complexities, among others. This research was therefore motivated by the need to address some of these limitations based on an automated system of product authentication. It is believed that legitimate brands can leverage such a system to protect their intellectual property, safeguard their reputation, and uphold the trust of their customers. Additionally, consumers can make informed purchasing decisions with confidence andwith the assurance that they are investing in genuine products.The research focused on theuseofa deep learning framework to achieve improved and efficient detection beyond what is obtainable in existing techniques. A system that utilizes an ensemble of CNN, Recurrent Neural Network (RNN) and Auto-encoderswas implemented as a panacea for achieving significant accuracy levels for classification and detection.The “small dataset challenge” which often leads to the scarcity of labelled training data and the risk of over-fitting was also addressed based on the application of augmentation functions such as image rotation, scaling, flipping, and colour manipulation. The technique supports the artificial expansion of the dataset to guarantee the multiplicity of samples for training the machine learning model coupled with the enhancement of generalization.There is also the gain of enhanced accuracy when confronted with previously unseen instances of fake clothes.

II. Literature Review

A fashion apparel detection using deep learning techniques to identify the fashion items worn or carried by individuals based on images from a dataset was presented in [12]. An extended R-CNN framework, incorporating geometric priors that encompassed various location and size parameters for a collection of fashion apparel items was used alongside an object proposals with a CNN. The CNN component was used to achieve image recognition and apparel classification. The framework proved suitable for enhancing accuracy and advancing apparel classification but failed for cases with limited or insufficient data and other constraints. A two-phase fashion apparel detection approach was presented in [21]. The approach adopted a two-phase YOLOv4 Two–Phase Detection (YOLOv4-TPD) method for fashion apparel detection. Data labelling and preprocessing was carried out and a two-phase training method was used for the implementation of the transfer learning. Experimental results showedthe ability of the method to attain improved image enhancement and detection accuracy, though with some computational complexities and inaccuracies. In [20], a cloth attributes detection model based on deep learning techniques was presented. The technique is a data-driven approach that emphasisesFeature Pyramid Network (FPN) for recognizing fashion quality and attributes. It is also based on low-resolution maps with large receptive fields making it possible to discern intricate clothing attributes. According to report, the model could be employed for identifyingthe quality levels of clothing items and categorizing clothing attributes in runway photos and fashion illustrations. Its challenges include addressing data imbalance and label inaccuracy.An attentive fashion grammar network for fashion landmark detection and quality grading was developed in [22]. Emphasis was laid on achieving a knowledge-guided fashion network to address visual fashion analysis challenges with a particular focus on fashion localization and classification.

Bidirectional Convolutional Recurrent Neural Networks (BCRNNs) enabled efficient message-passing over grammar topologies was used to achieve a well-structured landmark layout. The network encourages concentration on the functional aspects of clothing, acquisition of domain-knowledge-centered representations, and implementation of a supervised attention mechanism.The study in [23] focused on fashion apparel detection with the primary objective of identifying various fashion items worn or carried by individuals in a given image or dataset. The object proposal technique was combined with the deep CNN to expose the contextual and quality-based information from body poses. The experimental study demonstrated the effectiveness of the process for quality level detection for hats, glasses, bags, underwear, and shoes.In [24], a non-intrusive solution to the problem of distinguishing authentic products made by original manufacturers from counterfeit versions produced by fraudsters was presented. Supervised machine learning techniqueswere used to discern the microscopic attributes of genuine physical objects related to a product line and differentiate them from the microscopic features of counterfeit versions of the same product line. Experimental studies revealed the potential for high accuracy as well as performance and effectiveness issues.A CNN model for cloth classification and quality detection is presented in [25]. The model performs four distinct tasks within the realm of cloth classification; namely multiclass classification, attributes classification; retrieval of nearest neighbours, and quality detection. CNN was blended with data augmentation techniques such as image rotation and horizontal flipping for modifying the existing architectures with a view to tailor them for practical fashion classification. The simulation of the model exhibited good accuracy and its failure with inconsistencies with non-refined data. A deep learning technique for clothing quality recognition is presented in [18]. The technique encompassesconvolutional neural networks, YOLO v3 networks and other residual networks. The YOLO v3 network component was for the detection of clothing items in given images while the residual networks were useful for categorizing the color of clothing images. The study on the technique revealed its promising detection and categorization speed in addition to its non-encouraging performances under non-favourable lighting conditions and complex backgrounds. An RCNN framework for clothing quality detection was adopted in [26]. The framework adopted a modified selective search algorithm to extract the region of interest. It also uses the Inception-ResNet V1 model that incorporates the L-Softmax frameworkfor image depiction and categorization. Soft-Non-Maximum Suppression (NMS), a straightforward neural network was equally applied to rectify the boundaries of the region boxes. An extensive dataset comprising shirt images was curated to assess the framework's performance. The experimental study of the framework revealed it attained commendable overall labelling rates, with good precision and recall rates, though with significant computational requirements.YOLOv5s algorithm and Google Colab were combined to form a model for the quality detection and style recognition of clothes by the authors in [27]. Clothes image samples were selected from datasets containing fashion clothing through web crawling. The samples were categorized into plaid, plain, block, horizontal, and vertical. Performance validation was carried out using metrics such as average precision, mean average precision, recall, F1 score, model size, and frames per second. The experimental results demonstrated that YOLOv5s outperformed other learning algorithms in terms of recognition accuracy and detection speed.In [28], adomain knowledge clothing search system that acts as a virtual assistant capable of finding clothing items that align with fashion trends and meet the user's expectations based on availability in the real closet was introduced. All the essential garment and fashion knowledge were derived from visual images based on input desired image keywords, such as elegant, sporty, casual, and specific occasion. The clothing quality and fashion style recognition module searches for the desired clothing items from the database while the categorization process is based on supervised neural networking to group garments into distinct impression and quality categories. The neural network adopted warmness, loudness, and softness as the sensory attributes derived from color tone, print type, and fabric material. The experimental study of the model proved its ability to offer intelligent, user-centric fashion quality and style investigative services, though with some misleading results.

Though a great deal of study has gone into determining the quality of clothing materials, much improvement is still required to achieve a reliable basis for the separation of fake from real clothing. Most importantly, some of the existing models for clothes quality detection including those presented in [12, 17-20]are susceptible to complicated patterned fabric textures-induced failure, low dataset, low detection accuracy, wrongly labelled data and high computational complexities and requirements. The research gap created by these limitations justifies the need to develop a fake clothes detection system based on deep learning techniques.

System Architecture

The architecture of the proposed deep learning technique that combined Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Autoencoders for the detection of counterfeit clothing is presented in Figure 1.

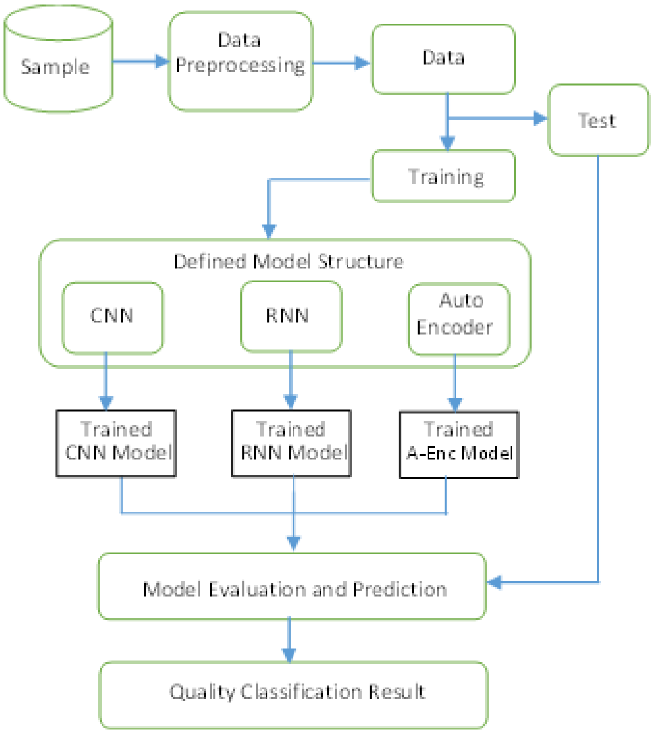

Figure 1: System Architecture

The architecture comprises dataset, pre-processing, data sampling, model training, evaluation and prediction as well as the classification units. The preprocessing unit prepares the images for training and testing by resizing the images to a uniform size, converting the images to grayscale, applying color normalization, and removal of unwanted information. Data augmentation formed the basis of the enhancement of the dataset's diversity. Following is the partitioning of the pre-processed dataset into training and validation sets. The training set provided the ground for training the CNN, RNN, and Auto-encoder while the validation set fostered smooth monitoring of the models' performance and the tuning of the hyper-parameters. During training, the images are subjected to the CNN operation for the extraction of germane features. The CNN involves multiple convolutional layers formulated for the use of filters to capture all local patterns and features. Next is the use of the pooling layers to reduce spatial dimensions. The resulting output from the convolutional layers is subsequently compressed and directed into fully connected layers for the classification operation. In view of the progressive nature of images, the RNN model contributed significantly to obtaining all the temporal dependencies and contextual information. At this phase, the training images are considered to be sequences of patches or regions while Long Short-Term Memory (LSTM) cells back-rolled the processing. The RNN model is trained to read the serial connections between the blotches, and its result is later processed via fully connected layers for classification. Stochastic gradient descent (SGD) optimization algorithms were used for the optimization of the CNN, RNN, and Auto-encoder models, along with their respective task-specific loss functions. For testing, the images were subjected to the same preprocessing steps as the training data. Each model subsequently and independently makes predictions on the testing images. The performance evaluation is based on accuracy, precision, recall, and F1 score which offer valuable insights into the system's capability to accurately differentiate between genuine and counterfeit clothing items. Ultimately, the output from the counterfeit clothing detection system is subjected to analysis and interpretation. This analysis encompasses an assessment of the individual model's efficacy and the identification of their respective strengths and weaknesses.

Pre-processing

The preprocessing is a critical stage in the CNN, RNN, and Auto-encoder-based model. It involves multiple stages for the preparation of the data for effective training and inference. The stages include the following:

***Data Normalization*:** Data normalization is performed to ensure that the input data has a consistent scale and range. The pixel values of the images are standardized to a common scale by rescaling them within the range of 0 to 1. It is used to reduce the impact of varying pixel ranges and enhances the convergence of the training process.
Resizing: Resizing the images to a consistent size is used to constrain all input images to the same dimensions, which is necessary for feeding them into the model. It is done by applying a fixed width and height to the images or by maintaining the aspect ratio while adjusting the longer dimension. Resizing the images facilitates efficient memory usage and computation in the subsequent stages.

Data Augmentation: During data augmentation, the images were subjected to random rotations, flips, translations, zooms, and brightness adjustment for the training set diversity enhancement, increased robustness and improved generalization.

***Feature Extraction*:**At this stage, the convolutional layers employ filters to capture local patterns and features, while the pooling layers reduce the spatial dimensions and mitigate over-fitting. The extracted features from the CNN are the quality attributes that form the meaningful representations that could be utilized for classification and analysis.

Deep Learning

The adopted deep learning technique encompasses algorithms and methodologies that promote the acquisition of patterns, predictions, and execution of tasks in a manner devoid of explicit programming. Statistical models and algorithms were harnessed for autonomous scrutiny and data deciphering as well asthe determination of applications across various domains for classification, regression, clustering, and recommendation. Three pivotal algorithms; namely Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Auto-encoder were adopted for fake cloth detection as follows:

Convolutional Neural Network (CNN): The architecture of the adopted CNN is presented in Figure 2. It comprises several convolutional, pooling, fully connected and dropouts. The convolution layer consists of a collection of separate filters, where each filter is individually convolved with the image based on the formula:

$$h_{i,j} = \sum_{k=1}^{m} \sum_{t=1}^{m} w_{k,l} . k_{i+k-1,\, j+l-1} \qquad (1)$$

m represents the kernel size, $h$is the convolution output,x is the input and w is the convolution kernel.

Pooling Layer: This is used to gradually decrease the size of the representation, computational complexity and the number of network parameters. The maxpooling operation is computed by moving the pooling window across the feature map. At each location (i, j) in the output h, the maximum value is obtained from the corresponding pooling window as follows:

$$h_{i,j} = \max\left\{x_{i+k-1,\, j+l-1} \forall 1 \le k \le m \; and \; 1 \; \le l \; \le m\right\} \qquad (2)$$

The pooling operation encompasses sliding a two-dimensional filter across each channel of the feature map and summarizing the features within the filter's covered region. For a feature map withdimensions$\boldsymbol{n_h}$ **x** $\boldsymbol{n_w}$ **x** $\boldsymbol{n_c}$, the resulting output dimensions, d after a pooling layer is obtained from:

$$d = \frac{n_h - f + 1}{s} * \frac{n_w - f + 1}{s} * n_c \quad (3)$$

$n_h$is the height of the feature map, $n_w$is the width of the feature map, n_c gives the number of channels in the feature map, f is the size of the filter and s is the stride length.

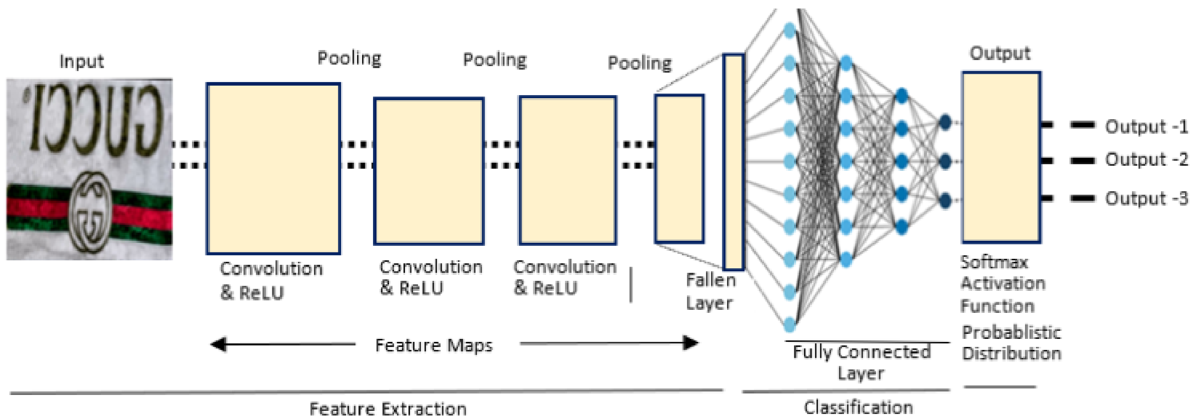

Figure 2: The CNN Architecture

Recurrent Neural Network (RNN)

RNN is a particularkind of ANN that mainly handles sequential data processing tasks such as natural language processing, speech recognition, and time series analysis. Its architecture is presented in Figure 3. In contrast to conventional feed-forward neural networks that process inputs in separation, RNNs feature recurrent connections that empower them to maintain information from prior inputs and integrate it into the existing computation. RNN is used to retain the internal memory or hidden state, which holds information on previous inputs in the sequence. The hidden state performs as a form of memory that incites the network to treat thearrangements of changingsizes. At each phase, the hidden state is updated and converted to input, in addition to the current input, for the network computations. RNN comprisesnumerous fixed activation function units, one for each time step. Each unit possesses a hidden state that represents the network's accumulated knowledge up to a specific time step. The hidden state is continuously updated at eachstep to manifest thenetwork trend of activities. The RNN computations of the current state, h_t is based on the formula:

$$h_t = f\ (h_{t-1}, x_t) \qquad (4)$$

$h_t$is the current state, $h_{t-1}$is the previous state and $x_t$is the input state. The activation function is applied as follows:

$$h_t = tanh\ (W_{hh} h_{t-1} + W_{xh} x_t) \quad (5)$$

W_{hh} gives the weight at recurrent neuron and W_{xh}represents the weight at input neuron. The output is obtained from:

$$y_t = W_{hy} h_t y_t \qquad (6)$$

$W_{hy} h_t$is the weight at output layer.

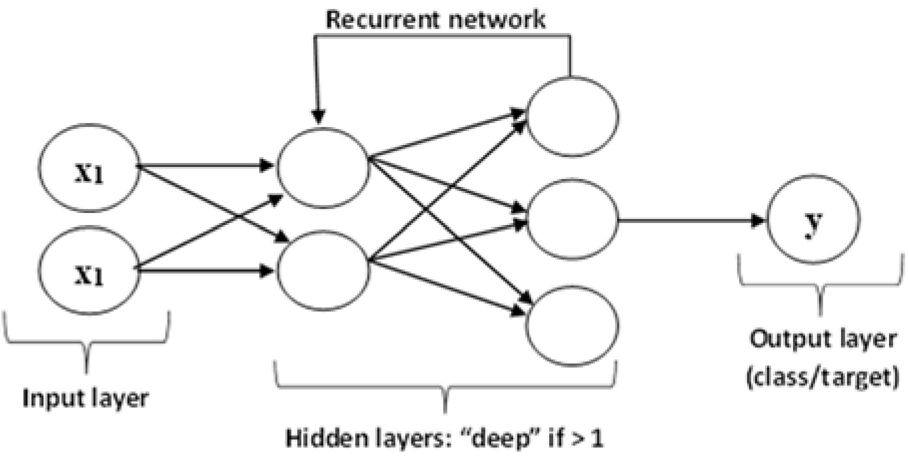

Figure 3: The RNN Architecture

Auto-encoder

An auto-encoder(architecture shown in Figure 4) is a particular class of artificial neural network designed for unverifiedor unsupervised learning and efficient data encoding. It comprisesan encoding function responsible for transforming the input data, and a decoding function which is responsible for reconstructing the input data via the encoded representation. Its primarygoal is to obtain a more efficient data representation required for dimensionality reduction. The auto-encoder consists of the following components:

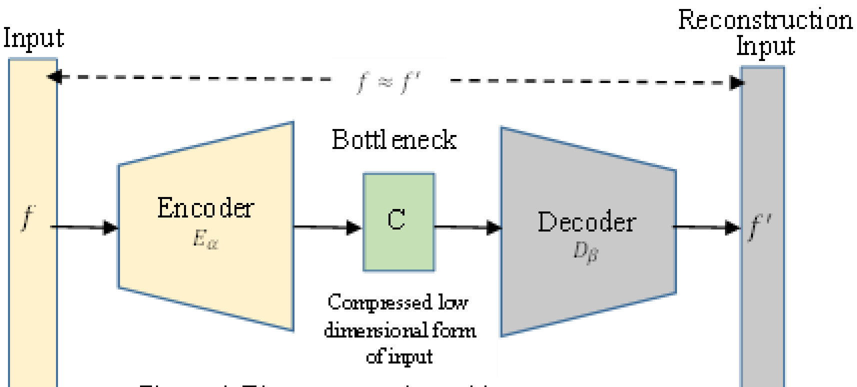

Figure 4: The auto-encoder architecture

Two set of messages: The first set is the decoded messages denoted as D, and the second set is the space of encoded messages denoted as S. Notably, D and S are Euclidean spaces, meaning that D = R^m , Z = R^n for some m, n.

Two parametrized families of functions: The first is the encoder family, denoted as $E_ø$: D → Z, which maps from D to S and is parameterized by ø; the second is the decoder family, denoted as $D_ø$: Z → D, which maps from S to D and is parameterized by ø which is the code or the latent variable. In the contrary, for any s ϵ S, $D' = D_ø(z)$ is the (decoded) message. Naturally, the encoder and the decoder represent the multilayer perceptron (MLPs where a one-layer encoder E_ø is presented thus:

$$E_ø(x) = \sigma(W_{x+b}) \qquad (7)$$

σ is an element-wise activation function in form of a sigmoid function or a rectified linear unit (ReLU). W is a weight matrix and b is a bias vector.

Training the Auto-encoder

The auto-encoder is trained to assess its performance. The training is characterized by a reference probability distribution, μref across R, as well as a renovation value function, f: R ∗ R → [0, ∞], where R = d (s, s')quantifies the dissimilarity between s` and s. The loss function of the encoder is formulated thus:

$$k(^{\theta}, ø) := E_{R\sim\mu ref}\left[f D_ø\left(E_ø(R)\right)\right] \quad (8)$$

The *optimal* auto-encoder for the specified task (μ_{ref}) is be expressed asarg min$L(^{\theta}, ø)$. The quest for the optimal auto-encoder is achieved through gradient descent. The reference distribution is the empirical distribution derived from a dataset{x_1…x_n} □ X, such that:

$$□ref = \frac{1}{N}\sum_{i=1}^{N} \delta_{zi} \qquad (9)$$

δ_{zi} is the Dirac measure and the quality function d(x, x`) = $||x - x`||_2^2$. The optimal auto-encoder is essentially a least-squares optimization minL ($^{\theta}$, ø), where L($^{\theta}$, ø) = $\frac{1}{N}\sum_{i=1}^{N} ||x_i - Dø\left(Eø(x)\right)||_2^2$.

The Experimental Study

The experimental study was carried out on a personal computer core i5 with 4GB RAM, 250GB HDD 205 GHz processor with 64-bit Operating System. The software requirements include Python libraries, Roboflow, Jupyter Notebook, Open CV, Matplotlib, Numpy and Python Image Library (PIL). Roboflow was used to streamline the training and deploying machine learning models for image and object recognition. It was also useful for data preprocessing, annotationand deployment. Jupyter Notebook is an open-source web application used to generate and disseminate documents encompassing live code, equations, visualizations, and textual content. The experimental dataset comprises a collection of images containing both real and fake cloth samplesobtained from Kaggle.com. The dataset was carefully curated to accommodate a diverse range of styles, colors, and patterns. The dataset was structured to achieve an equilibrium between authentic and counterfeit cloth images, thereby guaranteeing equality in the representation of instances from both classes. This ultimately mitigates the potential bias stemming from class imbalances. Towards achieving efficient processing and analysis, each image in the dataset was subjected to scaling for size and resolution uniformity as shown in Figure 5. Each image was assigned a corresponding label with a view to facilitate the training and evaluation of the detection algorithms. Authentic cloth images werelabelled as "1," while fake cloth images were labelled as "0".

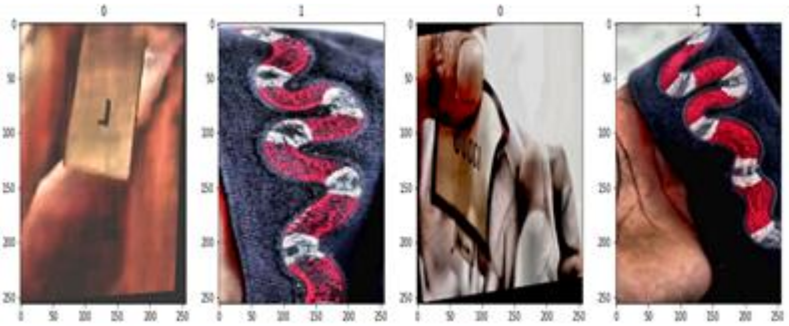

Figure 5: Scaled images

For the dataset's size expansion, data augmentation involving various random transformations was used. The augmentation process was used to mitigate the risk of over-fitting while enhancing the model's generalization ability. A rotation range of 15 degrees, translation ranges of 0.1 for width and height, a shearing transformation range of 0.1, brightness adjustments within a range of 0.5 to 1.5, and horizontal as well as vertical flips were used for the augmentation.

Data Preprocessing

The **tf.image.resize ()** function was used for image dimension specification and resizing during the preprocessing. Figure 6 presents the pots-resize images.

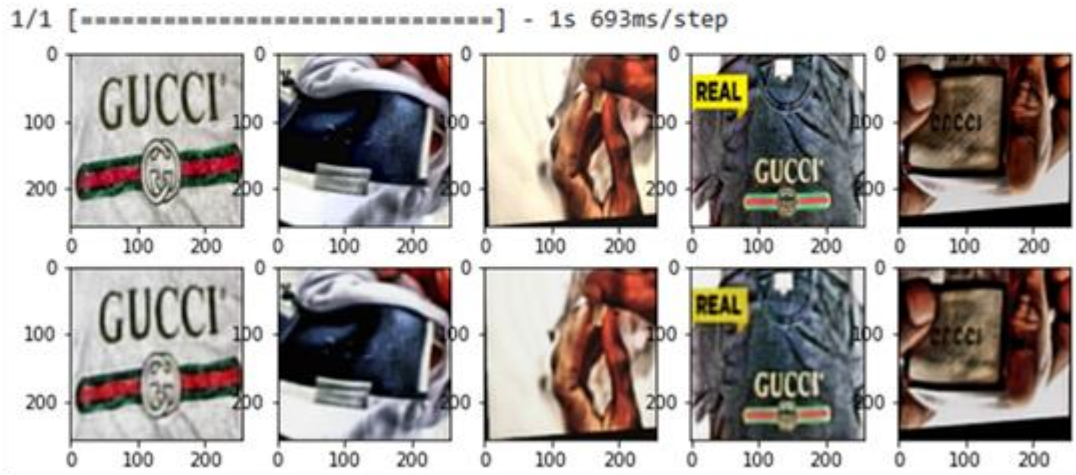

Figure 6: Multiple Resized Images

Feature Extraction

The output of the feature extraction operation is presented in Figure 7.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 254, 254, 16)	448
max_pooling2d_3 (MaxPooling2D)	(None, 127, 127, 16)	0
conv2d_4 (Conv2D)	(None, 125, 125, 32)	4640
max_pooling2d_4 (MaxPooling2D)	(None, 62, 62, 32)	0
conv2d_5 (Conv2D)	(None, 60, 60, 16)	4624
max_pooling2d_5 (MaxPooling2D)	(None, 30, 30, 16)	0
flatten_1 (Flatten)	(None, 14400)	0
dense_2 (Dense)	(None, 256)	3686656
reshape (Reshape)	(None, 1, 256)	0
lstm (LSTM)	(None, 1, 128)	197120
lstm_1 (LSTM)	(None, 128)	131584
dense_3 (Dense)	(None, 256)	33024
dense_4 (Dense)	(None, 1)	257

Total params: 4,058,353
Trainable params: 4,058,353
Non-trainable params: 0

Figure 7: Feature Extraction Interface

As shown in Figure 7, the convolutional layer has an input size of 256x256 with 16 filters (kernels), each of size 3x3 and 448 trainable parameters. The first MaxPooling2d layer operated with a pool of size 2x2 and reduced spatial dimensions of 127x127.The second MaxPooling2D layer operated with a pool size of 2x2 and reduced spatial dimensions of 62 x 62. The third MaxPooling2D layer operated with a pooling size of 2x2 and spatial dimensions of 30x30. The first Conv2D layer operated with input channels and 32 filters of size 3x3 with 4640 trainable parameters. The second Conv2D layer operated with 32 input channels and 16 filters of size 3x3 and 4624 trainable parameters.While the Flatten layers operated with dimension 30x30x16 tensor into a 1D vector of size 14400, the Dense layers were in 256 units and operated with 3,686,656 trainable parameters. At the Reshape layer, the output of the dense layer was reshaped into a tensor with shape (None, 1, 256). The Long Short-Term Memory (LSTM) layers 1 and 2 operated with 128 units but with 197,120 and 131,584 trainable parameters respectively. The total trainable parameters was 4,058,353.The result of the model (Figure 8) is classified into two classes 0 (classification figure < 0.5) and 1 (classification figure >= 0.5), where "10" implies fake while "1" implies authentic.

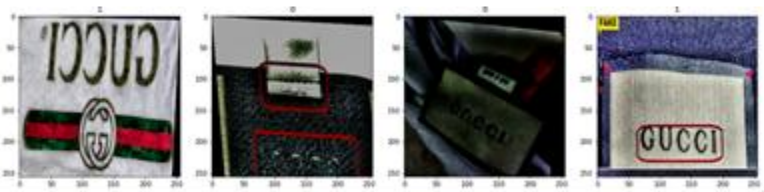

Figure 8: Sample of Output Images

PERFORMANCE OF CNN

Figure 9 and Figure 10showcase the plot of the performance of the CNN model in terms of loss and accuracy respectively. The model was subjected to training for multiple epochs, which are complete passes through the entire training dataset. Each epoch consisted of 7 batches, and each batch contained 32 samples. The training loss gradually decreased from an initial value of 1.3865 to a final value of 0.0118. This indicates that the model's predictions and classification improved over time, becoming more accurate. The training accuracy increased from 0.4732 to 1.0 (or 100%) in the final epoch. The model achieved perfect accuracy on the training data, indicating the correct classification of all the samples in the training set. The CNN model's performance was assessed on an independent validation dataset in which the loss consistently decreased, ultimately reaching a final epoch value of 0.0090. This implies that the model's predictions on unseen data improved consistently during training while the validation accuracy also improved, reaching 1.0 (or 100%) in the final epoch. Based on these, a perfect accuracy of the validation data was achieved. The evaluation of the model on different training and validation datasets produced a test loss of 0.0301, which further suggests the accuracy of the model.

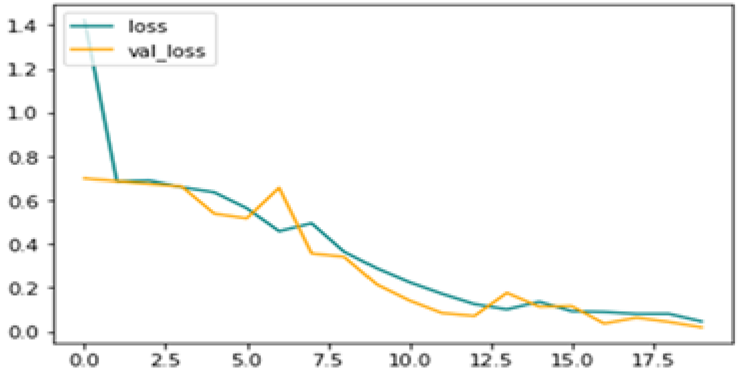

Figure 9: CNN Loss Graph

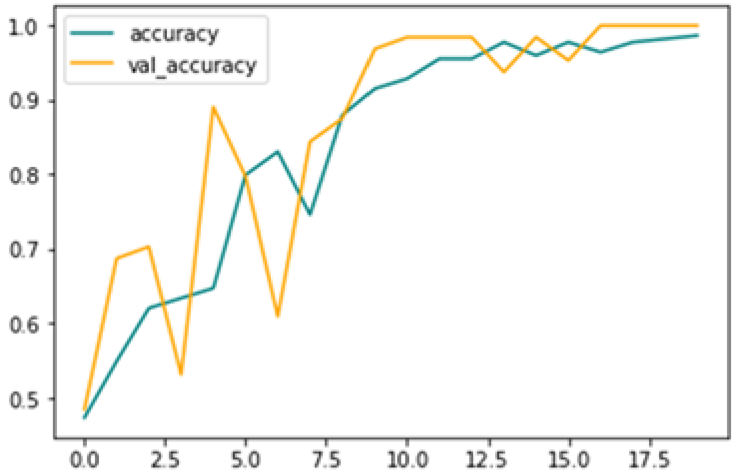

Figure 10: CNN Accuracy Graph

PERFORMANCE OF RNN

Figure 11 and Figure 12 present the plot of the loss and accuracy performance of the trained RNN model with 22 epochs. At the onset, the model's accuracy on the training and validation datasets was low. However, the accuracy gradually improves, signalling that the learning from the training data results in accurate predictions.After approximately 8 epochs, the accuracy experienced a growing and improving trend, indicating that the model could capture the underlying patterns and features of the dataset and ultimately refine its predictions sequel to time.The evaluation was premised on a separate test dataset with data not encountered during training. A test accuracy of 97% was achieved, indicating a correct classification and very strong generalization of all samples in the test dataset. Furthermore, the test loss was very low, suggesting that the RNN model predicted the test data accurately. A gradual improvement in accuracy throughout training indicates that the model's learning capabilities were effective, as it steadily refined its predictions with each epoch.

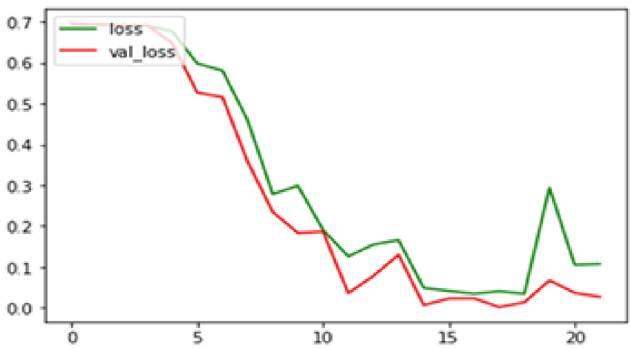

Figure 11: RNN Loss Graph

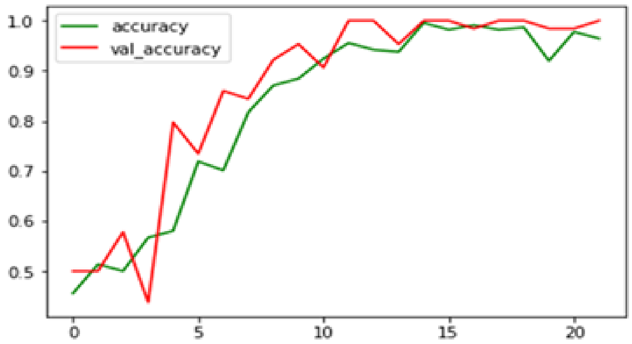

Figure 12: RNN Accuracy Graph

PERFORMANCE OF AUTO-ENCODER

Figure 13 and Figure 14 present the plot of the loss and accuracy performance for the auto-encoder model. The loss value for its epoch was 0.0087 and signifies the disparity between the model's predicted outputs and the true values. A lower loss value implies that the model's predictions closely align with the actual values, and hence a superior performance. With this epoch, an accuracy of 0.5625 was attained. For the loss, a modest value of 0.0087 was recorded showing that the model's predictions closely align with the actual values and a commendable performance interms of minimizing the disparity between predictions and ground truth.

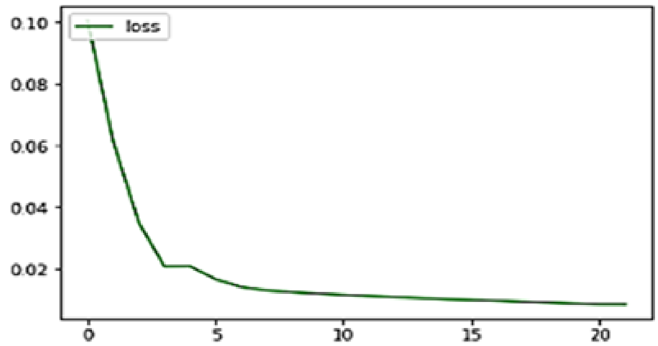

Figure 13: Auto-encoder Loss Graph

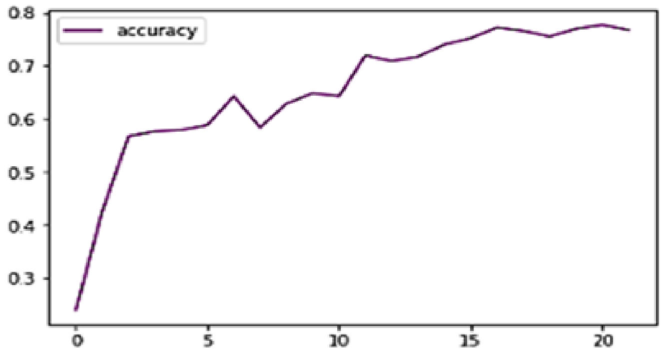

Figure 14: Auto-encoder Accuracy Graph

Performance of the Fake Clothe Detection Model

From the available results, the CNN model achieved perfect precision and accuracy for all samples in the dataset. While the RNN model also achieved perfect precision but with a slightly lower accuracy of 97%, the Auto-encoder model had a lower precision and accuracy compared to the CNN and RNN models with the correct identification of 63% of the positive instances. Figure 15 presents the comparative analysis of these results. Figure 16 and Figure 17 present the comparative analysis based on the loss graphs.

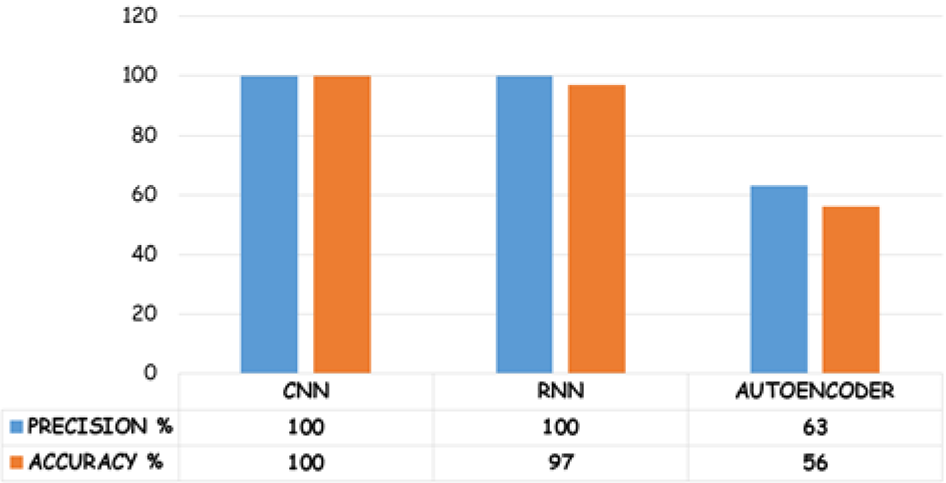

Figure 15: Comparative Analysis of the Model Result

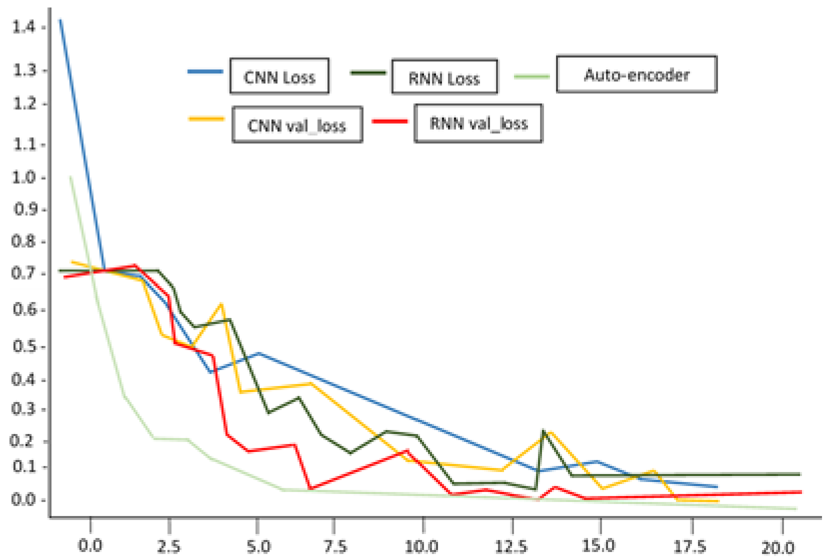

Figure 16: Comparative Analysis of Loss Graph

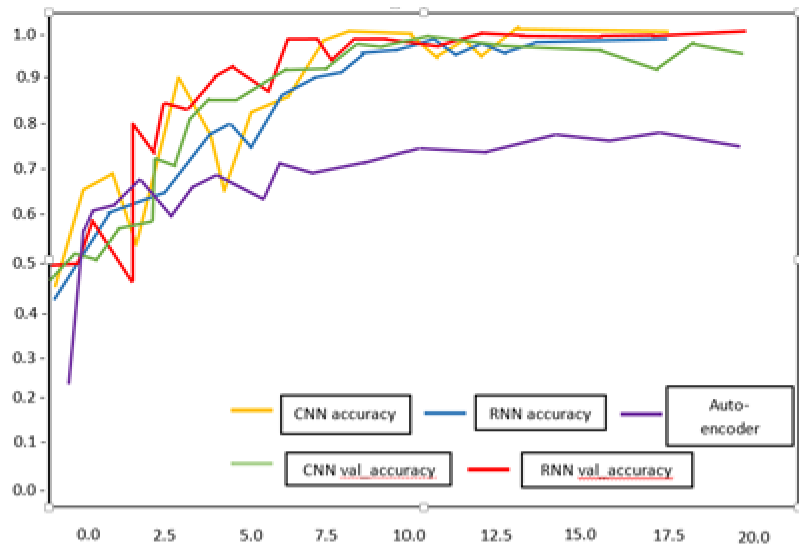

Figure 17: Comparative Analysis of Loss Graph

III. Conclusion

The study focused on a detailed study of counterfeit clothing detection-related literature, deep learning and other related topics in the research domain. A dataset of authentic and fake clothing images obtained from various online sources was used to investigate the performance of the proposed model. Images were labelled and annotated using Roboflow, a computer vision development tool for resizing and reformatting all images to achieve uniformity. The experimental dataset was divided into 3 sets of 70% training, 20% validation and 10% testing.The experimental study of the model highlightedits potential for accurate and seamless discrimination between real and fake clothing. The CNN and the RNN components of the model stood out with satisfactory performances in terms of loss minimization and prediction and classification accuracy. The auto-encoder exhibited limited performance which could be attributed to its unsupervised learning tasks like dimensionality reduction and feature extraction. However, the autoencoder still contributed in areas of input data reconstruction and unsupervised learning of compressed representation of the data. A deep learning framework was used to achieve improved and efficient detection beyond what is obtainable in existing techniques. The "small dataset challenge" which often leads to the scarcity of labelled training data and the risk of over-fitting was effectively addressed based on the application of augmentation functions such as image rotation, scaling, flipping, and color manipulation. There is also support for the artificial expansion of datasets to guarantee the multiplicity of samples for training the machine learning model in addition to feature enhancement. Analysis of results showed the model effectively handled complicated patterns and textures-induced failure and wrongly labelled data with complexity-free computations. This established that the new techniques had provided a way out of the limitations of some of the existing works on cloth counterfeiting detection. The model is therefore suitable for the protection of intellectual property, safeguarding of reputation, and upholding the trust of customers by legitimate brands in addition to consumers being able to make informed purchasing decisions with confidence and assurance on quality. However, there is still a need to consider the specific requirements of the fake cloth detection task when selecting the appropriate algorithm as well as broadening the training and evaluation dataset to encompass a wider variety of clothing types, fabric textures, and lighting conditions, which could potentially enhance the model's ability to generalize and improve its real-world performance.

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