yuvakṣhētṛa
Institute of Management Studies (YIMS)
Ezhakkad, Mundur, Palakkad - 678631, Kerala.
ACCREDITED BY NAAC WITH B+ GRADE (1st CYCLE)
Affiliated to the University of Calicut & Managed by the Diocese of Palghat

DEPARTMENT OF COMPUTER SCIENCE

ICACRI

INTERNATIONAL CONFERENCE FOR ADVANCED COMPUTATIONAL RESEARCH AND INNOVATIONS

2024

VOLUME I , ISSUE I

CONFERENCE PROCEEDINGS

English Language

Title of the Book	: International Conference for Advanced Computational Research and Innovations (ICACRI - 2024)
Editor	: JIBIN JOY
Published by	: Yuvakshetra Institute of Management Studies
Address	: Ezhakkad, Mundur, Palakkad, 678600
Rights Reserved	
First Edition	: FEBRUARY 2024
Cover Design	: JIBIN JOY
Printed at	: Jim Offset, Palakkad
Publishers	: Yuvakshetra Publications, Ezhakkad, P.O, Mundur, Palakkad
E mail	: yimspublication@yuvakshetra.org,
	: yuvakshetra@gmail.com
Website	: www.yuvakshretra.org
Tel	: 9400012368, 8714345789
Distributors	: Yuvakshetra Publications, Ezhakkad, P.O, Mundur, Palakkad
E mail	: yimspublication@yuvakshetra.org,
	: yuvakshetra@gmail.com

ISBN : 978-81-968246-5-5.

MODIFIED STAINNET ARCHITECTURE FOR STAIN NORMALIZATION NETWORK

A.Mahalakshmi 1 , Dr.P.Subashini 2

[1]*Department of Computer Science, Avinashilingam Institute for Home Science and Higher Education for women Coimbatore, India.*

21phcsf001@avinuty.ac.in.

[2]*Department of Computer Science, Avinashilingam Institute for Home Science and Higher Education for women Coimbatore, India.*

subashini_cs@avinuty.ac.in.

ABSTRACT

Normalization of stain often describes the transferring of color distribution from target image to source image and has been used to examine images in biomedicine. It is believed that traditional stain normalisation creates a pixel-by-pixel colour plotting approach that can't consistently perform style modifications between image databases since it's based on a single reference image. Though its complex network structure leads to low effectiveness in computation and artefacts in the style transformation, which has limited the real-world application in theory this deep learning techniques may effectively address the problem of style change. Here, A quick and reliable network called StainNet is used to absorb the colour mapping between the source and target picture, and distillation learning is utilised to simplify deep learning techniques. The dataset used is the images normalized using StainNET, Modified StainNet can learn the colour mapping association from a whole dataset and adjust the color value automatically. Here the modified architecture is analysed using Image augmentor package which is used to increase the dataset artificially based on the exsisting data. The AUC curve obtained is 91 percentage before augmentation and 93 percentage after augmentation. The results obtained from the Histopathology datasets demonstrate that StainNet, when updated, may perform on par with deep learning-based techniques.

Keywords: Stain Normalization, StainNET, Histopathology, Modified Architecture, Convoluional neural networks.

Introduction

Breast cancer is common in both men and women. As per the statistics conducted around the glob, It is observed that breast cancer has now over taken the lung cancer in female [1]. In the year 2023 a survey was conducted, in which in the United States, invasive breast cancer will be discovered in 297,790 women, while non-invasive (in situ) breast cancer will be found in 55,720 women [1]. Currently, there are over 3.8 million women in the United States suffering from breast cancer. In 2023, the sum of breast cancer fatalities in the United States is predicted to be 43,700 . The sixth most prevalent cause of mortality worldwide is breast cancer in women. It is projected that 684,996 women across the world would lose their lives to breast cancer in 2020. Breast cancer can be cured with the right analysis and handling. The kind of breast cancer and the extent of its extra-breast spread—to lymph nodes (stages II or III) or to other areas of the body (stage IV)—determine the course of treatment [2]. The symptoms for breast cancer is tumor in under arms or breast, nipple discharge etc.The diagnosis technique for breast cancer is core needle biopsy, Breast MRI, Ultrasound, Mammogram [3]. Core needle biopsy is done by removing a small piece of sample tissue from the tumor and examing it under the microscope. This examination is done by a pathologist. The study of tissue under microscope is know as histopathology.

Tissues or cells are habitually translucent in nature they need to be stained before viewing it under the microscope. The tissue are stained using Hematoxyline and eosin stains, where the tissue appears pink and nuclie appears blue. However, varied appearances of pathological pictures are frequently caused by variations in the stain chemicals, staining procedure, and scanner specs. These differences impair pathologists' judgement and degrade the functionality of CAD systems and the pathology apps that use them. Algorithms for stain normalization are suggested as a solution to these image-related problems. The other significant elements in the processed image are often preserved during the colour conversion process from the source to the destination image. According to some research, stain normalisation improves prediction accuracy for things like tumour categorization, therefore it's a crucial preprocessing step, particularly for CAD systems[10]. There are two categories of stain normalisation techniques: deep learning-based techniques and traditional techniques. In deep learning approaches, the colour mapping is learned from the complete dataset, but in conventional methods, one image is selected as the reference image to normalise the stain. So to learn the colour mapping from the entire dataset deep learning methods need large dataset. Smaller the dataset learning accuracy may be low. When the dataset is large the learning accuracy will be high. Additionally, the CAD system's performance will be superior to that of conventional or smaller datasets. A method for expanding the dataset is data augmentation. In order to increase model accuracy, generality, and control overfitting, machine learning techniques such as data augmentation include fabricating new data from actual observations. There are many predefined python packages for augmentation such as augmentor [4], which offers a high-level API for the stochastic, pipeline-based enlargement of picture data, effectively allowing real time image sampling from a distribution of enhanced images and many data augmentation techniques in literature [5]. It is an efficient and well-liked method for quickly generating extra training data or in situations when gathering new samples is impractical.The Augmentor project employs a pipeline-based, stochastic method for picture augmentation. By chaining together augmentation procedures like shears, rotations, and cropping, the pipeline approach allows the user to pass images through this pipeline and generate new data. The pipeline's operations are all applied stochastically, both in terms of the likelihood that they will be applied to each picture as it moves into and end of the pipeline and about the parameters for each operation, which, within user-specified parameters, are also created at random. In essence, this lets you select a sample from a collection of images that the pipeline may have generated in runtime. The package's goal is to offer a wide-ranging, highly customisable image augmentation library that is independent of any particular machine learning platform or architecture. The provision of really possible training data is essential for the effective use of augmentation, hence strict pipeline control is required when producing fresh data. As a result, Augmentor's operations are extremely parametric, giving users precise control over the creation of visuals. In this article a pretrained deep learning model StainNET [10] is modified in order to increase the breast tumor's categorization precision.

Background study

Stain separation and colour matching are examples of conventional procedures. The goal of colour matching techniques is to align the source image's colour distribution with the reference image's. Mecenko et al [6] found the stain vectors by singular value decomposition in optical density space. Where a pixel with the optical density value 0 represents no light was absorbed. The Pixels with OD value 0 is removed for stability reason. After using an adaptive process, the best results were discovered with a threshold value of $\beta = 0.15$. Using the geodesic direction, the shortest path between two unit vectors is determined. This technique, which is an integrated colour normalisation approach, doesn't need a target image.

Reinhard et al [7] is used to map the color distribution of target image to source image or under stained or over stained images. The mean and standard deviations in each color channel is equalized by linear transformation in lαβ color space. Next, the source picture receives the target image's mean. By using this technique, the source image's intensity fluctuations are guaranteed to be retained. This approach has the benefit that the original image's structure is maintained and that the contrast between the processed and destination images is the same. Finallydetermined the source photos' means and standard deviations before matching them in lab colorspace to a reference image.

Vahadane et al [8] computed the stain vectors using sparse non-negative matrix factorization. Stain separation method based on SNMF is proposed with integration of structure-Preserving color normalization algorithm. Sparsity constraints are added to NMF algorithm to capture the biological structure that are discrete. With this technique, the source picture's colours must be mapped onto the destination image.

Stain normalisation is mostly accomplished using generative adversarial networks (GANs) in deep learning-based techniques. StainGAN, an unsupervised stain normalisation technique based on CycleGAN, was suggested by Shaban et al. [9]. Without the aid of a subject matter professional, StainGAN learns everything from start to finish. StainGAN is utilised to do style switching amongst image datasets.

Hongtao et al. [10] based on StainGAN, presented StainNet, an unsupervised stain normalisation technique. Traditional stain normalisation techniques rely on a single reference picture and are unable to correctly convert the style of an image dataset. StainNet can modify the colour value pixel by pixel and learn the colour mapping from the entire dataset.

While deep learning-based techniques are effective in stain normalisation, their computational efficiency and resilience are not up to par. This article describes the modification of an existing stain normalisation network, called StainNET, to increase the tumor's classification accuracy. The updated design uses a completely 3 X 3 convolutional network to change the colour value. To study colour mapping, StainNET has been utilised as teacher network and the modified architecture is student network. According to the findings, StainNET that has been adjusted can perform comparably to StainNET[10].

Resource and Techniques

Dataset

The BreakHIS [12] dataset is publicly accessible dataset that is used.This dataset was collected from P&D Laboratory-Pathological Anatomy and Cytopathology, Parana , Brazil. The images in this dataset were taken with various lens magnification factors from 82 patients. This dataset is divided into two categories Benign and Malignant tumors, with 9,109 microscopic images. These two classes are further divided into 8 subclasses. There are 4 Benign types of tumor such as Adenosis,fibroadenoma,phyllodes tumor and tubular adenoma , 4 Maliganant types of tumor such as Ductual carcinoma, Lobular carcinoma,Mucinous carcinoma and papillary carcnoma in this dataset. The classification of the tumor is based on the structure of the tissue.

Since 400X gives better understating of the structure of tissue, there were 1821 samples from 400X Randomly 100 samples were used as training.The images that were visually appealing were choosen as target images. In this dataset the source and the target images are choosen randomly.

Modified StainNet for Stain normalization

There are two primary phases in this framework. StainNet must first be trained before it may generate modified StainNet, which consists of completely convolutional layers. Modified stainnet needs matched source and destination images in order to understand the transition from source to target colour space. In real life, it is rigid to obtain paired images and align them precisely. StainNet was adapted for use as a student network and utilised as a teacher network. whereby the output of StainNet is learned by the Modified StainNet via Binary Cross Entropy.

StainGAN is trained in two phases using two generators (G_1 and G_2) and two discriminators (D_1 and D_2) as part of the StainNet architecture. Images are transferred from source domains to target domains using G_1 and from target domains to source domains using G_2. To differentiate between an image produced by G_1 and an actual target picture, use D_1; to distinguish between an image produced by G_2 and an actual source image, use D_2. Comprising fully convolutional neural networks, the second phase is called Generation of StainNet. L1 loss is used by StainNet to learn the StainGAN output.

In the convolutional neural network , 3 X 3 kernal size is used in modified stainNET which is used to obtain the StainNET mapping connection. After every convolutional layer until the last, ReLU is used as a convolutional layer to increase the capability for nonlinear mapping. In order to achieve a compromise between computational economy and performance, we default to using three convolutional layers with 32 channels.

The two primary phases in the modified StainNet training procedure are as follows. First, we use unequal source and target pictures to train StainNET [10]. The raw pictures are then normalised using StainNet [10]. Lastly, the normalised pictures are used as ground truth to train the updated StainNet using the Adagrad optimizer and loss function binary cross entropy. Because the StainNet [10] mapping connection is dependent on the picture content, it will alter in response to variations in the image content.

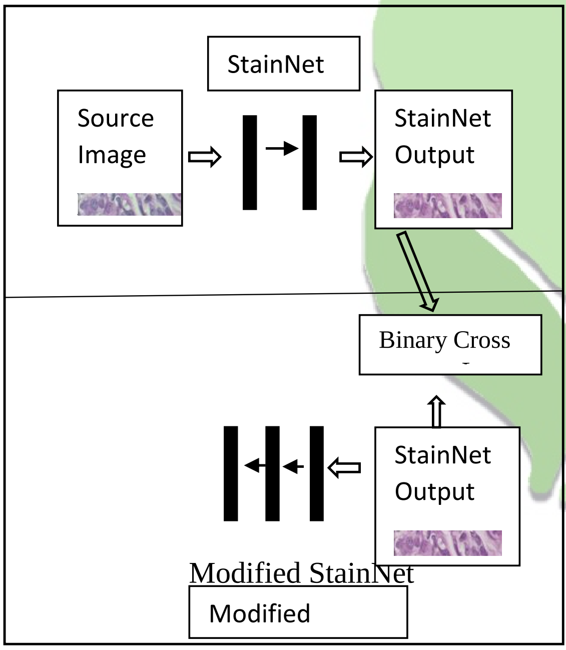


Figure 1: The above diagram represents the Architecture of the Modified StainNET. The Architecture of the Modified StainNET. The images are first normalised by StainNET from the source domain to the destination domain. Next, Modified StainNET is trained using the StainNET-normalized pictures as the Ground Truth.

While Training the modified stainNet it is observed that there was an overfitting problem. Due to which data augmentation was used to improve the image dataset. Here in this article Image augmentor an API based tool was used as augmentor [4]. Along with a variety of pre-processing methods that are routinely utilised, less common operations were also provided. Additionally, a significant number of functions have been added for your convenience that take into consideration standard augmentation methods.

Image augmentor is a pipeline based API and to use the augmentor we should begin with an empty pipeline. This pipeline's actions are added by the user in the order that they should be applied to the photos that are sent through it. The likelihood that each action should be done to pictures as they pass through may also be specified by the user. Additionally, the user defines the range of freedom of movement for each process. An picture or series of photos is continually fed through a pipeline once it has been created until the required number of new images has been produced. Every time an image passes through the pipeline, because to its stochastic nature, a distinct set of picture data is produced. With this stochastic method, even a modest beginning dataset may yield a potentially extremely huge number of pictures. Other transformations are also used, including perspective transformations and shearing across random axes and by random angles. Machine learning has been included into operations. For instance, because the photographs are appropriately cropped and subsequently enlarged to their original input size, random rotations won't result in images with translucent or black areas surrounding the recently rotated image. The shear and perspective tilt procedures work in the same way. Furthermore, Augmentor has the ability to do highly customisable random elastic changes. By selecting the grid size, the user determines the extent of distortions and the force of displacement inside the grid.

Result and Discussion

Implementation

Modified StainNET

For the StainNet, The stochastic gradient descent (SGD) optimizer, a batch size of 10, and an initial learning rate of 0.01 were used to train the model. The trained stainGAN was used to minimise the difference between the network's output and the normalised picture by applying L1 loss. To decrease the learning rate from 0.01 to 0 across 300 epochs, the Cosine Annealing Scheduler was used. Using the learned StainNet, normalise the source pictures in the training and testing datasets before applying the updated StainNet. Following normalisation, the photos are utilised as training groundtruths. Adagrad optimizer, learning rate of 0.003, batch size of 10, and 10 epochs were used to train the modified StainNet. During training, the model with the lowest test loss was assigned the weights that corresponded to it.

Data Augmentation

We want to use Image Augmentor to ensure that our network is trained with new versions of our data each time. The ImageAugmentor receives a batch of input pictures before randomly rotating, translating, and other effects each image in the batch. Then augmentation was carried out utilising random rotations and zoom operation. The zoom operation was used to learn all the possible features in the image. Where the degree of rotation and number samples for the rotation was specified. There is a probability parameter for each operation at least. For the rotation operation, this was set to 0.7, and for the zoom operation, to 0.3. In order to produce the data, the sample function is finally run, producing 300 fresh samples for CNN's training.

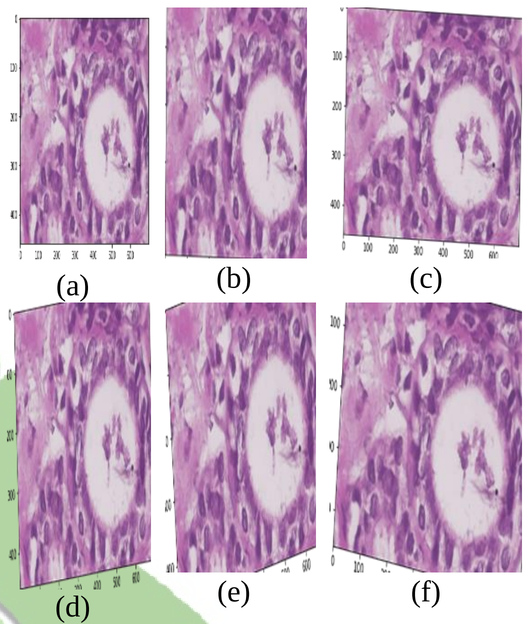


Figure 2 : Above is the few sample images obtained for Rotation operation and zoom operation using ImageAugmentor.

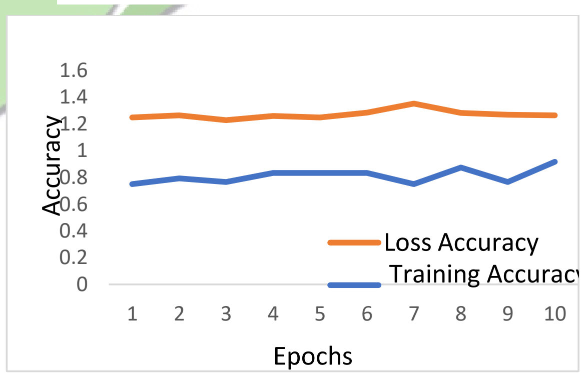


Figure 3 : Above is the training accuracy graph obtained for modified stainNET Before augumentation.

Modified StainNet , StainNet and StainGAN are compared in classification application. The AUC obtained using StainGAN is 0.90, 0.89 using StainNet and 0.91 Using Modified StainNet. The aforementioned findings demonstrate that Modified StainNet may successfully increase the classifier's accuracy and that the Modified StainNet method's and StainNet method's performances are similar.

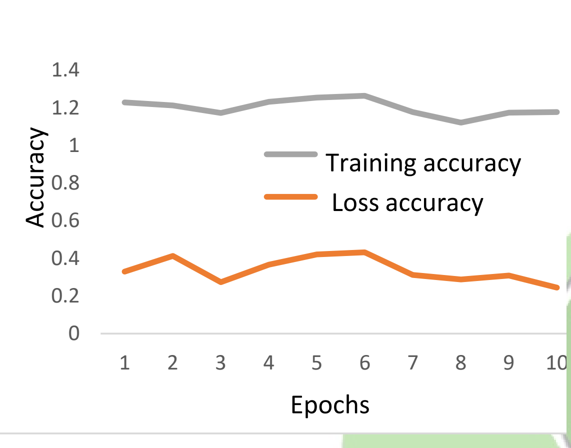


Figure 4 : Above is the training accuracy graph obtained for modified StainNET After augmentation.

The AUC obtained after data augmentation is 0.93 % for modified StainNET. As compared to earlier i.e the AUC obtained for modified StainNET before augmentation is 0.91% and After augmentation is 0.93%. It can be concluded that if augmentation is done then the then classification accuracy has improved effectively.

Conclusion

Stain normalization is considered as one of the important preprocessing step in classification of breast tumor. Though StainNet is better normalization technique from the literature, since it is good at preserving the information of the image. The architecture of the StainNET can be modified using 3 X 3 convolutinal neural network instead of 1 X 1 convolutional neural network. The AUC results obtained was better when the architecture of the StainNET was modified. It can be concluded that the existing StainNET architecture can be modified as mentioned in the implementation section for better classification accuracy.

Acknowledgement

The AI tools used in this article is Paraphrasing. The paraphrase is used for the purpose of evaluation and updation of the content in the article. The percentage of AI tool report obtained is solely the responsibility of the author for the publication of the article.

Reference

[1]https://www.cancer.net/cancer-types/breast-cancer/statistics

[2]https://www.who.int/news-room/fact-sheets/detail/breast-cancer

[3]https://www.mayoclinic.org/diseases-conditions/breast-cancer/diagnosis-treatment/drc-20352475

[4] Bloice, Marcus D., Christof Stocker, and Andreas Holzinger. "Augmentor: an image augmentation library for machine learning." *arXiv preprint arXiv:1708.04680* (2017).

[5] Chlap, Phillip, et al. "A review of medical image data augmentation techniques for deep learning applications." *Journal of Medical Imaging and Radiation Oncology* 65.5 (2021): 545-563.

[6] Macenko, M., Niethammer, M., Marron, J. S., Borland, D., Woosley, J. T., Guan, X., ... & Thomas, N. E. (2009, June). A method for normalizing histology slides for quantitative analysis. In *2009 IEEE international symposium on biomedical imaging: from nano to macro* (pp. 1107-1110). IEEE.

[7] Reinhard, E., Adhikhmin, M., Gooch, B., & Shirley, P. (2001). Color transfer between

images. *IEEE Computer graphics and applications*, *21*(5), 34-41.

[8] Vahadane, A., Peng, T., Sethi, A., Albarqouni, S., Wang, L., Baust, M., ... & Navab, N. (2016). Structure-preserving color normalization and sparse stain separation for histological images. *IEEE transactions on medical imaging*, *35*(8), 1962-1971.

[9] Shaban, M. T., Baur, C., Navab, N., & Albarqouni, S. (2019, April). Staingan: Stain style transfer for digital histological images. In *2019 Ieee 16th international symposium on biomedical imaging (Isbi 2019)* (pp. 953-956). IEEE.

[10] Kang, H., Luo, D., Feng, W., Zeng, S., Quan, T., Hu, J., & Liu, X. (2021). Stainnet: a fast and robust stain normalization network. *Frontiers in Medicine*, *8*, 746307.

[11] Hameed, Zabit, et al. "Breast cancer histopathology image classification using an ensemble of deep learning models." *Sensors* 20.16 (2020): 4373.

[12] BreakHIS Dataset Link : https://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis/

IMAGE ENCRYPTION AND DECRYPTION USING ADVANCED ENCRYPTION STANDARD (AES)

B.Nandhini
II-MSc Information Technology
Avinashilingam Institute for Home Science
And Higher Education for Women
Coimbatore, India
nandy20020324@gmail.com

D.Shanmugapriya
Department of Information Technology
Avinashilingam Institute for Home Science
And Higher Education for Women
Coimbatore, India
shanmugapriya_it@avinuty.ac.in

ABSTRACT

The Image Encryption Decryption application is a Python-based image processing tool with a Tkinter graphical user interface and the OpenCV library. It empowers users to select an image, perform encryption to convert it into grayscale, and subsequently decrypt it. The edited image can be saved locally, and there's an option to reset it to its original format. The implementation utilizes various libraries, including OpenCV, NumPy, PIL, and PyCrypto, with the Tkinter GUI facilitating image encryption and decryption through randomly generated keys. The encryption process involves a simple division of the input image, while decryption consists of multiplying the encrypted image, ensuring a reversible transformation. Additionally, the application computes the Peak Signal-to-Noise Ratio (PSNR) to evaluate the quality of the decrypted image. Employing the Advanced Encryption Standard (AES) algorithm, the program integrates Tkinter for GUI and Pillow for image processing, with OpenCV handling the image encryption and decryption operations. The user-friendly interface allows seamless interactions for opening, encrypting, decrypting, resetting, and saving images, offering a comprehensive solution for secure image handling. The calculated PSNR metric provides users with valuable insights into the fidelity of the decrypted image compared to the original.

Keywords— Image Encryption, Tkinter GUI, OpenCV, AES Algorithm, Peak Signal-to-Noise Ratio (PSNR).

I. INTRODUCTION

Encryption is the process of converting plaintext into ciphertext, which is a scrambled and unreadable form of the original data. The purpose of encryption is to protect the confidentiality of data by ensuring that only authorized parties can access and read it.

There are several encryption algorithms and techniques available, ranging from simple substitution ciphers to complex cryptographic algorithms like Advanced Encryption Standard (AES). These algorithms use mathematical functions and keys to transform plaintext into ciphertext.

Decryption, on the other hand, is the process of converting ciphertext back into plaintext. Only those who possess the correct decryption key can reverse the encryption process and access the original data.

Overall, encryption and decryption are crucial components of data security and are used to protect sensitive information in various industries, such as finance, healthcare, and government.

A. ENCRYPTION AND DECRYPTION IN IMAGE

Encryption and decryption of images involve converting the image data into a format that is not easily readable by anyone who does not have the decryption key. This is done to protect sensitive image data from unauthorized access or tampering.

The encryption process involves applying a mathematical algorithm to the image data using a secret key. This transforms the image data into an encrypted form that is not easily readable by unauthorized parties. The decryption process involves reversing the encryption process using the same secret key to retrieve the original image data.

Various encryption algorithms that can be used for image encryption, such as Advanced Encryption Standard (AES), Data Encryption Standard (DES), and Blowfish. These algorithms vary in their level of security and complexity.

In addition to encryption, various techniques can be used to enhance the security of image data, such as steganography, which involves hiding encrypted data within other files, such as images or audio files. Overall, image encryption and decryption are important techniques for protecting sensitive image data from unauthorized access or tampering.

B. NEED FOR IMAGE ENCRYPTION AND DECRYPTION

Encryption and decryption of images is important for several reasons, including:

Privacy and confidentiality: Image encryption ensures that confidential information in images such as personal information, medical records, and classified government information cannot be accessed by unauthorized persons.

*1) **Protection against tampering**:* Image encryption makes it difficult for attackers to tamper with the content of an image, thus protecting against data modification or manipulation.

*2) **Intellectual property protection**:* Encryption of images ensures that the ownership and copyrights of the images are protected, and they cannot be copied, replicated, or distributed without proper permission.

*3) **Secure transmission**:* Encryption ensures secure transmission of images over networks such as the internet, making it difficult for attackers to intercept, view, or modify the images during transmission.

II. LITERATURE REVIEW

This part of the article presents some of the most recent literature works carried out to detect and classify Table I.

TABLE I. OVERVIEW OF LITERATURE REVIEW

Study	Title of the paper	Author	Year Published	Algorithm applied
[1]	DeepEDN: A Deep-Learning-Based Image Encryption and Decryption Network for Internet of Medical Things	Yi Ding	2021	Deep-learning-based image encryption and decryption network (DeepEDN)
[2]	Improved Chaos-Based Cryptosystem for Medical Image Encryption and Decryption	Mohamed Gafsi	2020	Chaos-Based Cryptosystem

[3]	FPGA Implementation of Improved Security Approach for Medical Image Encryption and Decryption	Amal Hafsa	2021	MAES (Modified Advanced Encryption Standard)
[4]	Symmetric keys image encryption and decryption using 3D chaotic maps with DNA encoding technique	Sakshi Patel	2020	Multilevel encryption algorithm
[5]	A Survey of Image Encryption Algorithms	Manju Kumari	2017	Chaotic schemes, substitution-permutation networks (SPN), and Feistel network-based algorithms.
[6]	An RGB image encryption using a diffusion process associated with a chaotic map	Manish Kumar	2015	RGB image encryption and decryption
[7]	Fixed-time Synchronization of Complex-valued Memristive BAM Neural Network and Applications in Image Encryption and Decryption	Manman Yuan	2020	RGB image encryption and decryption, using a complex-valued memristor-based BAM neural network (CVMBAMNN)
[8]	Medical image encryption based on improved ElGamal encryption technique	Dolendro Singh Laiphrakpam	2017	ElGamal encryption technique
[9]	A new image encryption scheme based on hybrid chaotic maps	Ahmad Pourjabbar Kari1	2021	Grayscale image encryption scheme based on hybrid chaotic maps
[10]	An image encryption scheme based on the chaotic tent map	Chunhu Li	2016	Chaotic tent map

III. METHODOLOGY

A. *Problem Definition*

Image encryption and decryption is the process of converting an image from its original format to a scrambled or encrypted format using a mathematical algorithm to prevent unauthorized access to its contents. The encrypted image can only be decrypted and viewed by authorized persons with the proper decryption key.

The need for image encryption and decryption arises due to the widespread use of digital images in various applications such as medical imaging, military operations, and personal data storage. These images contain sensitive and confidential information that requires protection against unauthorized access and manipulation.

The main challenge in image encryption and decryption is to ensure that the encrypted image is secure and cannot be easily decrypted by unauthorized persons.

Therefore, the encryption algorithm must be complex and robust enough to withstand attacks from hackers.

Image encryption and decryption is an essential process for protecting sensitive and confidential information contained in digital images. With the increasing use of digital images in various applications, the need for secure image encryption and decryption techniques is becoming more critical. Therefore, there is a need for continued research and development in this field to improve the security of image encryption and decryption algorithms.

B. Overview Of The Project

The project is a Python-based web scraping tool that extracts data from a website and stores it in a CSV file. The purpose of this tool is to automate the process of collecting data from a website, which can be time-consuming if done manually.

The tool uses the Python Requests library to send HTTP requests to a website and retrieve the HTML content of the web pages. The BeautifulSoup library is then used to parse the HTML content and extract the relevant data, such as the title, author, and content of articles.

The tool is designed to be flexible and customizable, allowing the user to specify the website to scrape, the specific data to extract, and the format of the output file. The user can also specify additional parameters, such as the number of pages to scrape or the delay between requests, to control the scraping process.

The scraped data is stored in a CSV file, which can be easily imported into other applications, such as spreadsheets or databases, for further analysis. The user can specify the name and location of the output file, as well as the delimiter used in the CSV file.

One potential application of this tool is in the field of data journalism, where journalists can use it to collect data from public websites and analyze it for news stories. It can also be used for academic research, market analysis, or any other application that requires the collection and analysis of data from a website.

Overall, this project provides a powerful and flexible tool for web scraping that can be used for a wide range of applications. Automating the process of collecting data from a website, can save time and effort for users who need to collect and analyze large amounts of data.

C. AES ALGORITHM

AES is a symmetric block cipher that encrypts data in 128-bit blocks, using a secret key that can be 128, 192, or 256 bits long. It operates on a 4x4 matrix of bytes called the state, which is initialized with the plaintext block to be encrypted.

The AES algorithm consists of several rounds of transformations that are applied to the state, with the number of rounds depending on the key length. Each round consists of four steps: SubBytes, ShiftRows, MixColumns, and AddRoundKey.

- In the SubBytes step, each byte in the state is replaced with another byte from a fixed lookup table called the S-box.
- In the ShiftRows step, the bytes in each row of the state are shifted cyclically by a certain number of bytes.
- In the MixColumns step, each column of the state is multiplied with a fixed matrix.
- In the AddRoundKey step, each byte in the state is XORed with a corresponding byte from the round key.

After the final round, the resulting state is the encrypted block. The decryption process is similar but uses the inverse operations of the SubBytes, ShiftRows, and MixColumns steps, and the round keys are applied in reverse order.

The exact implementation of the AES algorithm can vary, but the core principles remain the same.

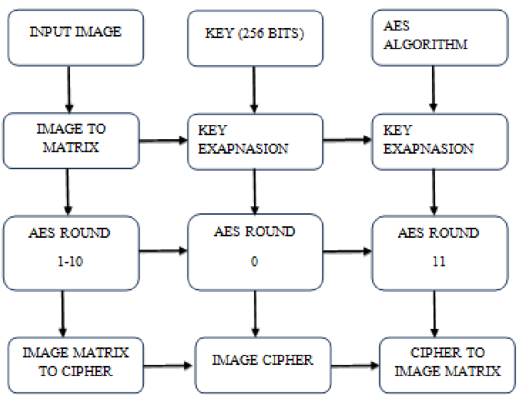


Fig. 1. AES Algorithm Architecture

D. ENCRYPTION

Encryption is a technique of converting data into a form that can only be read by authorized parties. It is the process of converting plain text into an unintelligible form of data called cipher text. The purpose of encryption is to ensure the confidentiality and security of sensitive information, such as passwords, credit card numbers, and other personal or business information. Encryption involves the use of an algorithm, a set of rules that convert plain text into cipher text, and a key, a unique code that is used to unlock the cipher text and convert it back to plain text.

One of the key benefits of encryption is that it provides a way to protect data in transit or at rest. For example, when a user logs into a website or sends an email, their information is sent over the internet in an unencrypted form, which makes it vulnerable to interception by cyber criminals. By encrypting the data before it is transmitted, the information becomes unreadable to anyone who does not have the key to decrypt it. Similarly, encryption can be used to secure data that is stored on a device or server, so that even if the data is stolen, it is not accessible without the encryption key.

There are several types of encryption algorithms, including symmetric key encryption, asymmetric key encryption, and hashing algorithms. Symmetric key encryption uses a single key for both encryption and decryption, while asymmetric key encryption uses two keys, one for encryption and one for decryption. Hashing algorithms are used to create a unique digital fingerprint of a piece of data, which can be used to verify that the data has not been tampered with.

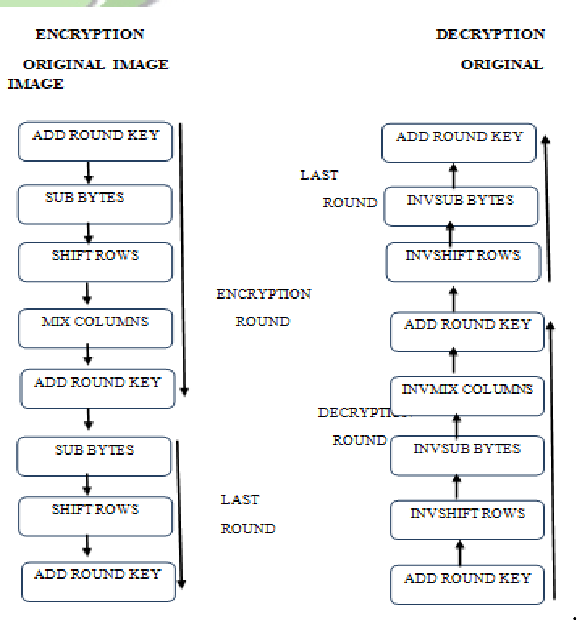
E. DECRYPTION

The decryption of an image involves converting an encrypted image back into its original form using a decryption algorithm. Encryption of an image is done to ensure its confidentiality and prevent unauthorized access to it. However, there may be instances where an encrypted image needs to be decrypted to be accessed or used. The decryption of an image involves reversing the encryption process by using a decryption key to transform the encrypted data back into its original form.

There are various methods of decrypting an image depending on the encryption algorithm used. The decryption process usually involves the same algorithm as the encryption process but with the decryption key instead of the encryption key. The decryption key should be kept secure and should only be accessible to authorized persons.

One of the most common encryption methods used for images is the Advanced Encryption Standard (AES). AES encryption uses a symmetric-key block cipher that encrypts data in blocks of 128 bits. To decrypt an AES-encrypted image, the same key used for encryption is required. The decryption process involves reversing the steps used in the encryption process. AES decryption can be done using various software tools that are readily available online.

In conclusion, decryption of an image involves converting an encrypted image back into its original form using a decryption algorithm. The decryption process requires a decryption key that should be kept secure and accessible to authorized persons only. The most common encryption method used for images is AES, but other encryption methods such as Blowfish, Triple DES, and RSA can also be used. The choice of encryption method depends on the level of security required and the specific use case.



IV. CONCLUSION AND FUTURE SCOPE

This project is a simple image encryption and decryption tool built using Python and several libraries such as Tkinter, PIL, and OpenCV. The application allows users to select an image file, encrypt the image using a randomly generated key, and then decrypt the image using the same key.

The encryption process involves dividing the image into small blocks and then multiplying each block with a corresponding block from the generated key, while the decryption process involves multiplying the encrypted image with the key to recover the original image.

The application also includes features such as resetting the edited image to its original format and saving the encrypted image. Overall, this project demonstrates the basic concepts of image encryption and decryption and provides a simple tool for users to experiment with these concepts.

In the future, this project could be expanded to include additional features such as more advanced question-answering capabilities, improved natural language processing, and integration with other technologies such as chatbots or voice assistants. It could also be trained on more data to improve its accuracy and performance, and potentially be used in a variety of applications such as customer service, education, and healthcare.

ACKNOWLEDGEMENT

This work is supported by the Centre for Cyber Intelligence, Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, Tamil Nadu, India for the infrastructure support for implementing the project.

REFERENCES

[1] Yann LeCun, Yoshua Bengio & Geoffrey Hinton (2015). Deep learning. Nature, 521, 436-444. doi:10.1038/nature14539.

[2] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[3] Karpathy, A. (2016). The Unreasonable Effectiveness of Recurrent Neural Networks. Retrieved from http://karpathy.github.io/2015/05/21/rnn-effectiveness.

[4] Brownlee, J. (2020). Deep Learning for Natural Language Processing. Retrieved from https://machinelearningmastery.com/deep-learning-for-nlp/

[5] Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language Models are Unsupervised Multitask Learners. OpenAI blog. Retrieved from https://openai.com/blog/better-language-models/

[6] Lample, G., & Conneau, A. (2019). Cross-lingual language model pretraining. Advances in Neural Information Processing Systems (NIPS), 4694-4705.

[7] Devlin, J., Chang, M.W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171-4186.

[8] Shih, C. Y., Liao, W. Y., & Yu, H. T. (2017). A review of machine learning-based decision support systems for diabetes disease diagnosis. Journal of Medical Systems, 41(8), 129.

[9] Akhtar, M. S., & Imran, M. (2019). A survey of machine learning techniques for smart healthcare. Journal of Ambient Intelligence and Humanized Computing, 10(5), 1649-1665

[10] Miotto, R., Wang, F., & Wang, S. (2018). Medication recommendation using multiple instance learning and concept embedding. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 2308-2317).