

Automatic Pill Recognition and Recommendation System Using Deep Learning techniques

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Abstract. Medication stability is necessary to avoid problems in day-to-day Human care. According to recent studies, prescribing errors are one of the most serious problems in fitness. It is LASA mistakes, which are the most common. Prescription tablet images can be accurately identified based on their visible appearance, ensuring patient safety and allowing patients to use modern healthcare devices. Several business studies have addressed the tablet identity problem, with solutions primarily based on content-based image retrieval (CBIR) and image analysis. The few-shot mastery issue, on the other hand, regularly inhibits correct tablet popularity in everyday life. Existing LASA prevention strategies are not without flaws. This project aims to develop technologies that can help users correctly distinguish prescription tablets from photographs. We recommend an automatic type device for tablet images using deep learning in this project. The proposed type was implemented using the deep learning set of rules of the DCNN and RPN. The choice of futurization for the molecules is an essential step in developing deep learning systems for tablet type and era. This version exceeded typical computer imaginative and visionary solutions in terms of identifying pills and capsules, as well as preventing medication errors. The project's outcome can be utilized in the real world to help patients recognize tablets and capsules, as well as to prevent medicine errors caused by look-alike pills, with an accuracy of more than 90%.

Keywords: Medication errors, Medication stability, CBIR, Tablets, Deep Learning, RPN, LASA, Errors, DCNN, Capsules, Pills.

1. Introduction

The average population age is incrementing, (WHO) report [1] released in October 2017, the world's chronic population is expected to be over 285 million people, with 140 million of them being elderly adults over 50 and 110 million suffering from numerous chronic diseases. The fact that a person's physiology deteriorates with age is generally known. These vulnerable visually impaired senior persons are more prone to take the wrong prescriptions. Alternatively, they may forget to take their medication if they are on any.



A patient, on the other hand, has no way of knowing whether the meds he or she is taking are accurate. Because of the great range of drugs used for chronic disease patients, classification is a difficult task, and medication misidentification due to neglect may result in the patient receiving the incorrect medication. Taking the wrong medicine might cause hazardous action or counteract the drugs' intended benefits, resulting in more significant outcomes like acute complications.

2. Related Work

"For White-Pill Identification, Luminance Compensation based on Background Shadow," by So chart Chokchaitam. This study suggests luminosity compensation based on a background shadow to lessen the influence of luminance intensity on the Y tablets. The value Y of the backdrop grows as the luminance intensity increases while the value Y pill shadow diminishes dramatically. As a result, we can leverage the link between the selected pill's values and the difference between the Y values

of the back drop and its shadow for brightness compensation. "The PillID Data set is a fine-grained, low-shot pill identification" by Naoto. ePillID that incorporates option that is realistic. Use the bench mark as a starting point for experimenting with different approaches. Standard photo classification algorithms and metric learning-based techniques are included in the baseline models. According to error analysis, these models are still unable to identify between confusing pill consistently. "IoMT based Pill Dispensing system," by Ujjwal Singh project aims to build a low-power, cost-effective because the data can be utilized in vital applications, despite the fact that security issues have not been properly addressed in the past, and this fact motivates us to deliver their quire answer. By requiring direct engagement with a doctor and certifying data only after his or her consent, this study hopes to prevent data miner predation. This paper's proposed health care model has a multi-layer architecture (3 layers). The architecture is made up of three layers: sensor network, dispenser, and public display. A clock in real-time is connected to the pill dispenser, which keeps track of the date and time. To achieve correct findings, sensor sensors used to picture tablets may need to be placed or calibrated. A data processing problem occurs when continuous real-time readings are displayed. Constant usage of hardware can lead it to overheat, resulting in a temporary shutdown. "IoMT based PillID is dispensing system", by Seungtae Kang Images obtained from two various brands of smartphones both indoors and outdoors were used in this project. 200 different sorts of pills were collected, with at least 10 images taken for each pill. Back-lighting is corrected and Linear regression is used to approximate the fluctuation in light. The color difference on the surface of the pills is erased in the result image. "Co for Des: An Invariant Feature Extractor for the Drug Pill identification" by Mateus A The proposed method of a pill classifier that extracts features from pills focused on their shapes & color (Co for Des). The author offers an extractor that is based on the form and color of the object for identifying pill images that are invariant to rotation (Co for Des). From the input image's conversion, the suggested approach starts with the pill segmentation stage. Following pill contour use mentation and detection, shape properties are extracted. These mentation procedure's contour is used to calculate the color property. Using moments that are invariant and Hu, the contour center point of the segmented pill is calculated.

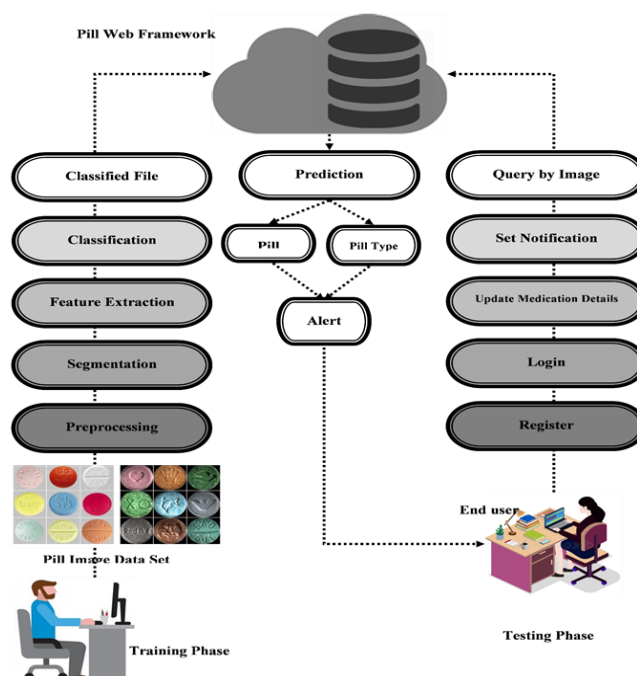
Wan-Jung Chang (Member, IEEE), Liang-Bi Chen (Senior Member IEEE), Chia-HaoHsu, Jheng - Hao Chen, Tzu-Chin Yang, and Cheng-PeiL in published "Med Glasses: A Wearable Smart-Glasses-Based Drug Pill Recognition System Using Deep Learning for Visually Impaired Chronic Patients." In this research, we targeted at ensuring safe medication use. Medication data is uploaded to cloud-based management platform by the Med Glasses system track the medication status. "Deep Learning with Hyperspectral and Ordinary Camera Images for Automated Drug Recognition," says the author. John D. Mai, Ph.D., TejalGala1, Yanwen Xiong2, Min Hubbard2, Winn Hong2, John D. Mai, Ph.D., Yanwen Xiong2, YanwenXiong2, Yanwen Xiong2, Yanwen This study use proprietary, low-cost CMOS camera combination, CNN algorithms trained to identify ordinary camera images, and hyperspectral images to have an early comparison. Using 2D CNN, VGG-16, we were able to detect four kinds of over-the-counter pain medication with over 90% correctness. Due to changes in matrix size were able to correctly identify four different sorts of drugs 100 percent of the time. Preliminary Investigation of a Neural Network-Based Multi-Convolutional Model for Identifying Pill Images Using Classification Rules In this study, to recognize pills using classification rules, they developed a multi-convolutional neural network (CNN) model. Because basically all pills have three key identifiers: colors, shape, and imprint, a multi-CNN architecture was used. Each identification is characterized by three CNN models. A total 24,000 images were collected, with 95% of the data set that establish pill classifications, the outcomes of each CNN architecture are processed according to predetermined rules. "Lighting Variability Correction for Pill Identification," Seungtae Kang, Gil-Jin Jang, and Minhoo Lee School of Electronics Engineering Kyungpook National University, Daegu. This research primarily provides an over strategy for compensating for differences in light. If this method is used to find reliable approximates the class activation mapping (CAM) generated from the result (CNNs) gives values for the shaded parameters tomato for each of the shading conditions. They used shading remuneration to improve the surface photo of the pill photos in this work. Ranjitha Dept. of Electronics and Communication Engineering SMVITM, Bantakal Udupi, India Swati Shri pad-Kulkarni Dept. of Electronics and Communication Engineering SMVITM, Bantakal Udupi, India Rashmi KH Dept. Of Electronics and Communication Engineering SMVITM, Bantakal Udupi, India Athma shree AT Dept. of Electronics and Communication Engineering SMVITM, Bantakal Udupi, Indi, "Color and Shape Recognition of Pills using Image Processing" In this paper, they use a Raspberry Pi and a camera to determine the color and shape of the pill. The color and shape of the corresponding pill will then be displayed on the LCD screen. "A Deep Learning-Based Intelligent Medicine Recognition System for Chronic Patients," Wan-Jung Chang (Member, IEEE), Liang-Bi Chen (Senior Member IEEE), Chia-HaoHsu, Tzu-Chin Yang, and Cheng-PeiL in. ST-Med-Box, a smart drug detection software based on deep learning, is proposed in this work.

The technology can help chronic patients incorrectly taking multiple medications method can currently distinguish between eight different medicines. According to the findings of the testing, the recognition accuracy is around 80%. As a result, the proposed technique has the potential to significantly reduce the problem of drug interactions produced by a variety of medications. Existing System. Non-computer vision-based approach There are various internet platforms available, such as the US National Library of Medicine's 'Pillbox,' Medscape's 'Pill identifier,' and Web MD's 'Pill identification tool,' are now accessible to assist in pill identification. Users must manually enter or select from drop-down menus several characteristics of the pill in question, such as its shape, color, and the On these internet sites, there may or may not be imprints and scores. Draw back First, the options in the drop down menu might not cover all of the things you're looking for. This is especially true for colour selections, as it is impossible to characterize each hue and it stones as a continuum characteristic. Second, manual data entry, such as color interpretation, is subject to user subjectivity. Third, manual inputting can be time consuming, particularly when there are multiple pills to be identified. Computer vision-based approach.

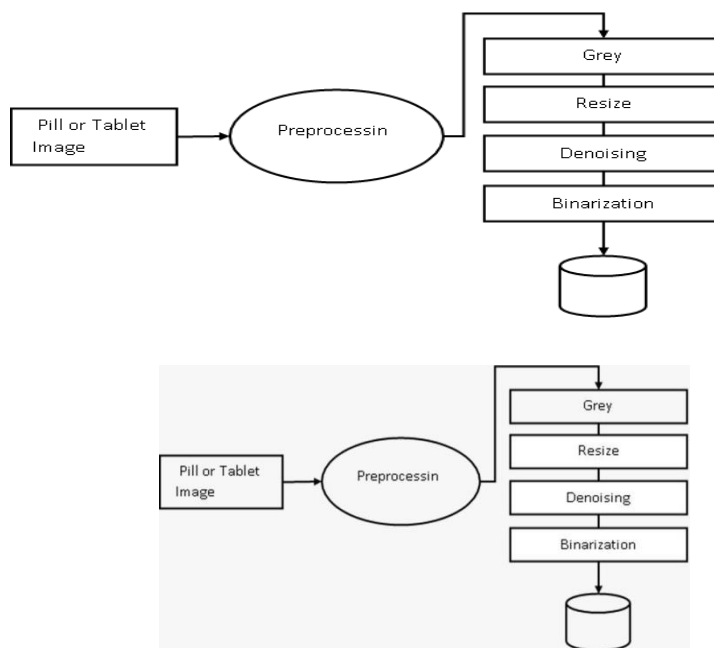
Hue, saturation, and value are the most common colour characteristics (HSV) colour profiles due to their resistance to illumination change. Two Feature (SIFT) and (MLBP). Classification algorithms Weight parameters extracted during the pre-training stage a readjusted and optimised using Back Propagation (BP) neural networks. A type of supervised training method is the BP algorithm. To achieve classification results, support vector machines (SVMs), Sparse DE noising Auto-Encoder, and logistics of tax regression algorithms were utilised (SDAE). Draw back Ina controlled environment, manually developed features work well, but in un constrained conditions, similar as images taken with mobile phones, they are prone to misidentification and have poor binary and multi-class classification performance on a short spectrum sample set.

3. Proposed system

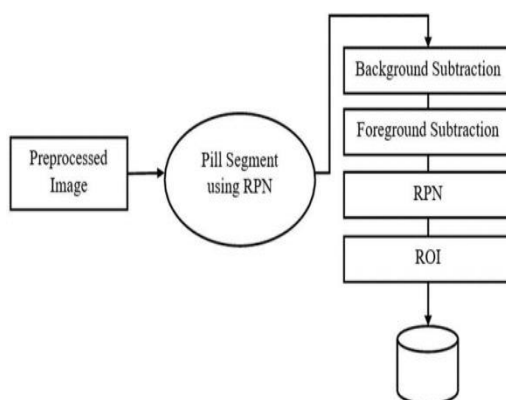
A Deep Convolutional Network(DCN) for the identification of oral pills is proposed. Once given the image, deep learning algorithms typically consist of three steps: Finding the pill(s) in the image, Cropping the pill(s), and Classifying the cropped image. To discover the pills in an image, we'll use an RNN object detection model, and to classify the photos, we'll use a CNN image classifier. Produced using object detection and classification model Advantages Due to its hard inductive bias, CNN performs better in low data regimes; DCN achieved superior results in pill identification when compared to existing methods. A cost-effective technique for quickly identifying and verifying pills Higher accuracy, speed, and reliability Ability to pick upon subtle differences. System Architecture:



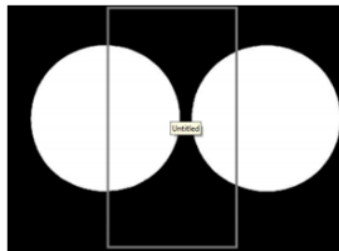
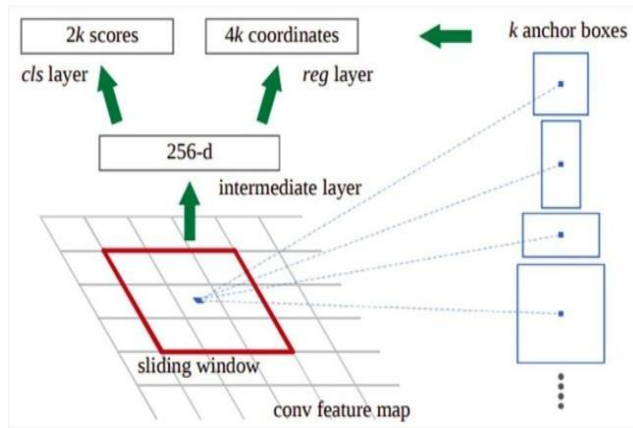
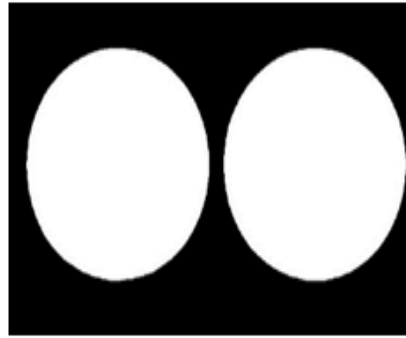
Collection The pharmacy delivered a total of 400 regularly used tablets and capsules. There are meds for the heart and lungs (28.5%), central nervous (18.8%), stomach (9.2%), endocrine (8.8%), in flammation (7.7%), plasma and nutrition (6.9%), muscular system (6.7%), respiratory system (6.3%), gastrointestinal (3.5%), immune cells and malicious disease (0.6%), dermatology (0.2%), and many others (2.9 percent). The pills were divided based on their dose forms, imprints, sizes, and color. Pill or Tablet Identifier in this module, we develop a web app using Bootstrap that helps you distinguish medication. Websites dedicated to pill recognition were created to assist consumers in distinguishing between different types of pills and avoiding unpleasant medication reactions. We are concentrating on developing are the liable system that can reliably identify pills using the pills data base. Pill Image Dataset Acquisition as the first step in the big data approach, big data acquisition intends to massive amount of data in a range of formats, employ distributed platform Testing Phase-Pill Image in this module the end-user inputs an image to predict the pill name and regarding information. Import the single pill images of a pill type from the pills test data set. The pills are masked and have a black background. There are two images per single pill type, which are the front and back of the pills. The front images are labeled with 0 and the back images are labeled with in the file name. When a pill is chosen to be the candidate to be located in a vial image, a random choice is made between the front and back of the pill. Pre-processing: The pre-processing procedure in this module improves the quality of the Pill or tablet images and prepares them for further processing by the end user. It also helps to improve the quality of pill images. The characteristics include improving the signal-to-noise ratio, theses the tic appearance of pill images, removing irrelevant noise and the back drop of unpleasant are as, smoothing regions of the inner part, and maintaining relevant edges.



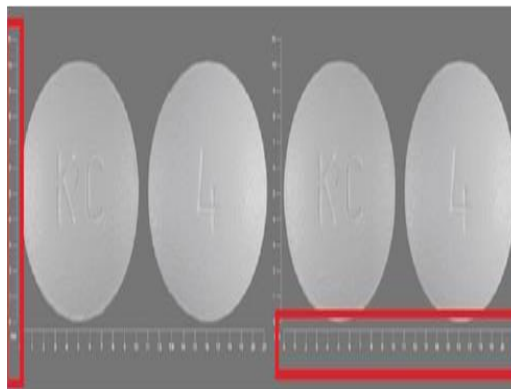
We will utilize a median filter in our proposed work to improve image smoothing and reduce computing complexity. However, it outperforms the mean filter in terms of preserving relevant visual detail. It replaces each pixel image with the median of the surrounding area's pixel values. In comparison to the the median filter has two major advantages. It's a more accurate prediction than the average. The median is un affected by asking a leurre presentative pixel in a neighborhood. The median does not generate any crazier pixel values because it must be the value of one of the pixels in the neighborhood. Segmentation is a procedure in which an image is partitioned in to various sections in this module. Allow Store present a full image region. S is divided into p subregions, such as S1, S2, S3, Sp, during the segmentation process. Certain criteria must be met, such as complete segmentation (every pixel must be contained within the region), connectivity (every point with in the region must be connected in some way), and disjointness of the regions.



The region growth (RG) method is used to segment images. The methodology for region growth and current related work region growing are explained in this paper. RG segmentation algorithm that uses region seeds. Only the " intensity" constraint is employed to evaluate surrounding pixels in a classic region-growing approach. A three hold level for intensity value is chosen. RPN: A (RPN) is a fully convolutional network that simultaneously predicts object limitations and object test scores a teach location. From start to finish, the RPN has been extensively trained to CNN's feature, with an Anchor Point for each feature (point) on the map. The image's anchor point matches to the feature map's anchor point, thus these anchor boxes are centred there. Feature Extraction in the features extraction extract feature techniques are utilized to the pill's shape, size, colour, and imprint are used to extract features. Shape Identification for pill shape identification, the pill shape must be extracted and recognised from the supplied query pill image (logical1) and the back drop will be represented in the black region in the final query pill image (logical0). Despite the fact that must be cropped from the centre in order for the recognition system to be trained. Using previous knowledge from the pill picture collection, the front and rear sides of the pill are separated. According to a careful examination of the dataset, the search zone for cropping the pill images ranges 37 and 67 percent.



To find the cropping site, a horizontal-vertical line (equal to the image height) is moved pixel by pixel The fore ground is clipped. Size Identification The picture, as seen in Figure, includes information about the pill's size (in mm). It is critical to develop a system for auto magically.

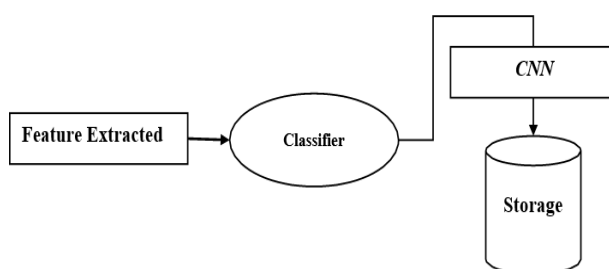
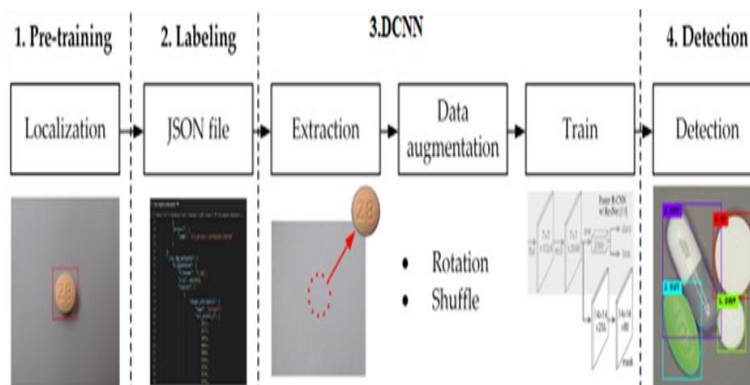


Prepare a binary three hold image with to establish the size of the query pill (logical 0). Because the graph scales in the pill picture collection are already white, a high three hold of 0.90 is found to be sufficient. The height and width of the pill are then calculated using the connected components of the threshold binary picture component have a value other than 1. The

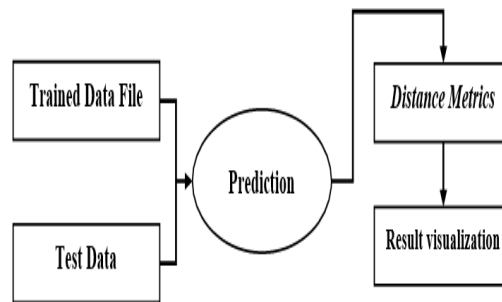
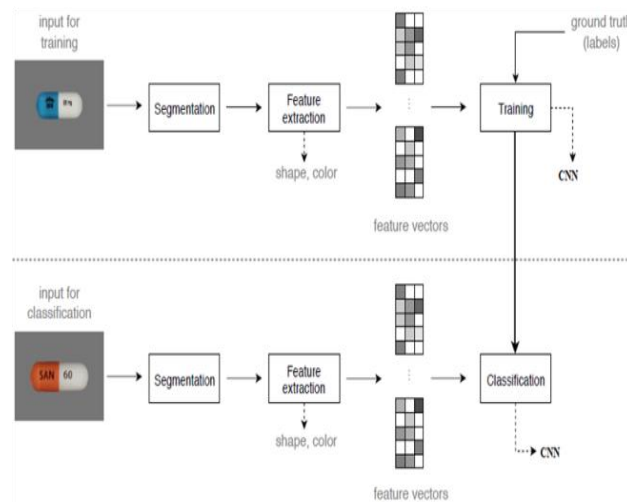
value of the connecting components in this circumstance determines the height of the pill under discussion. The width of the pill is calculated using a similar method, which entails sweeping a virtual horizontal line from bottom to top. The pill's size is saved as an area. The query pill's area is calculated using the computed height and width information, as well as the shape information acquired during the shape identification stage. Color Identification Mask pictures created from the shape recognition step are utilized to determine the color of the pill picture in the input query. After cutting the input question pill image in the same way as Previously, the binary mask image was multiplied by the pill image's colored front and back sides. Because the mask value is 1 for the pill form region and 0 for the rest of the area, for each R G B color. To obtain three color values, the average of each color channel is determined, that can be used for color identification. Imprint Identification Pre-processing is done to boost the quality of the pill picture so that imprints on the tablet may be recognized and identified. After that, the (MSWT) applied to the pill imprint may be found. At the same time, the thresholding method is applied to the question pill's front and rear side cropped pictures. Taking the average of all pixel values in the image yields an appropriate threshold. Following that, the picture is converted to binary representation. In most situations, after converting to binary, the back ground is preserved at logical 0 (black) to logical 1 (white).



The pills used in this study come in a wide range of colors, shapes, sizes, and imprints. Furthermore, because the contrast and brightness of the tablets in the sample vary greatly, the imprint algorithm produces above that are extremely exact, while others are only adequate. As a result, the extracted pill imprint is correctly identified using a NN. DCNN Classification: Deep Convolution Neural Network Classifier The CNN classifier is most commonly used for image and video recognition. The CNN has the ability to learn the necessary data characteristic on its own. The CNN performs tasks such as receiving numerous inputs, computing the total of their weights, sending output to the activation function, and returning the needed output. The pill images' critical qualities, such as form, size, color, and imprint, are automatically able to detect with better accuracy using CNN classification.



Prediction The matching process is carried out in this module using the test Pill Classified file and the trained classified result. The difference is calculated using Hamming Distance, and the prediction accuracy is shown as a result.



Re commendation System A web-based prototype system was developed in this module. The following steps can be used to operate the system by the hospital, doctors, patients, and researchers: Insert a visual image of a pill or tablet. Confirm a Tablet name and type of tablet to be used; After this, the system lists potential pharmacies or medical shops and manufacturers to buy.

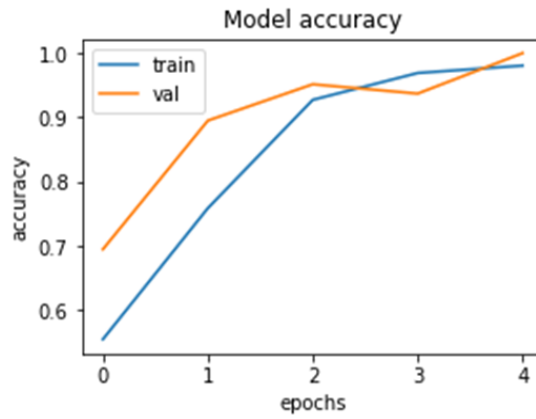
4. Experimental outcome

The following are the key points about performance measures that are presented in this project's context: True Positive (TP): A pill exists, and the name of the pill has been discovered by the algorithms. False Positive(FP): Even if no pill is present, the algorithms identify it and show the pill name. False Negative (FN): A pill exists, but the algorithms are unable to recognize it or its name. True Negative(TN): No pill has been taken, and nothing has been found.

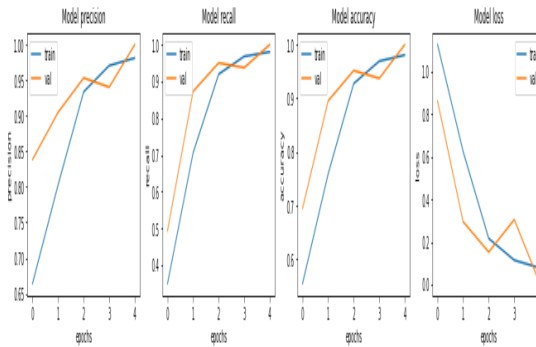
| | True (relevant) | False (not relevant) |
|--------------------------|-----------------|----------------------|
| Positive (retrieved) | TP | FP |
| Negative (not retrieved) | TN | FN |

Accuracy is a metric for determining whether or not a model/algorithm has been appropriately trained and how well it operates. In this thesis, accuracy refers to how successfully it detects persons in an underwater environment. The formula for determining accuracy is:

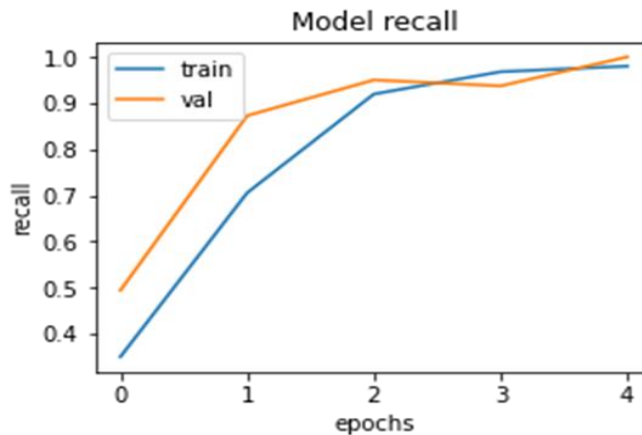
Accuracy will be = $(TP+TN) \div (TP+TN+FP+FN)$



Precision It is the proportion, positively forecasted situations that turn out to be true positives. Precision, in the context of this thesis, refers to the percentage of objects in the undersea environment that are anticipated to be humans but are humans. The following formula is used to calculate the precision. $Precision = TP / (TP + FP)$



Recall It's the proportion of actual positive instances to expected positive cases. In the context of this thesis, recall refers to the percentage of people who are correctly identified as humans. The following formula is used to calculate recall. $Recall = TP / (TP + FN)$



F1Score It's also referred to as a balanced F-score or an F-measure. The F1 score, which combines precision and recall, is a measure of a model's accuracy. A good F1 score, in the context of this thesis, indicates that there are fewer false positives and false negatives. This demonstrates that the model successfully recognizes humans in an underwater setting.

If the F1 score is 1, a model/algorithm is considered perfect. The following formula is used to calculate it.

$$F1 = 2 \times (Precision \times Recall / (Precision + Recall))$$

Precision: 0.9990234375

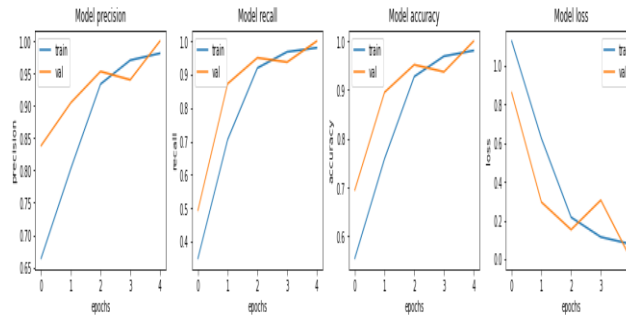
Recall: 0.9964285714285714

F1_score: 0.9977122020583142

Training time

In this thesis, the time spent training is referred to as training time it takes to train the chosen machine learning algorithms on the data set. **Prediction Speed** In this paper, speed is a statistic that is used to determine how long it takes the algorithms to

process and recognize an impediment. Loss Function Loss function, which optimizes network weights on features retrieved at many resolutions rather than only at the pixel level, to conduct feature matching between the truth and the result of the segmentation network.



5. Conclusion

Our goal was to demonstrate how a deep learning network based on convolution, with a mechanism of operation that is quite similar to human image identification skills, can capture and explain 'look-alike' errors. After that, you can apply an acceptable method for obtaining subtler nuance differences in discriminating between look-alikes things. The conclusions of this study, with an accuracy of more than 90%, may be implemented in the actual world. Supporting pharmacists in recognizing pharmaceuticals and preventing Medication mistakes caused by identical blister packages. The exceptional performance of DCN illustrates the Deep Learning model's potential in the detection and recognition of pills. In the future, packets will need to be identified.

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