Artificial intelligence-based Medicine Recognition System using faster Recurrent Convolutional Neural Networks

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Abstract: Recently, chronic patients are taking multiple medications incorrectly and taking the wrong medications due to similarity of drugs. It is possible that taking the improper medication can result in hazardous interactions with other medications or they will counteract the intended benefits of the medications, resulting in extra severe repercussions such as acute complications. The conventional methods are failed to provide the maximum efficiency. Therefore, this article is focused on implementation of faster recurrent convolutional neural networks (FR-CNN), which is capable of extracting the features from images. FR-CNN mainly used to analyze the patterns of the medicines and extracts the deep features. Further, classification of medicines is carried out by comparing with ground truth labels. The simulation results shows that the proposed system resulted in superior performance as compared to state of art approaches.

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1. Introduction

Today, population around the globe is ageing. Among many of the world’s 7.5 billion elderly, there are 600 million individuals, of whom 480,000 are permanently impaired. Such as World Health Organization (WHO) estimates [1], 1.4 chronic diseases harm the ordinary elderly and 5 times the usual medications of an aged individual. The common elderly is afflicted by 1.3 chronic diseases. Seniors are now 7 times more likely to take the incorrect drug when their neurological roles are diminishing. The WHO further states that one-third of deaths worldwide are attributed not only to illness itself, but rather to the excessive usage of medicines, with an expense of almost USD 28.5 billion per year [2]. Among all the world’s 7.5 billion elderly, there are 600 million individuals, of whom 480,000 are permanently impaired. Thus, according WHO, chronic illnesses impact the normal elderly and a traditional elderly person’s drug intake is five times that of a juvenile. Seniors are now 7 times more likely to take the incorrect drug when their neurological roles are diminishing [3]. The WHO further states that one-third of deaths worldwide are attributed not only to illness itself, but also about the excessive usage of medicines, with an expense of almost USD 28.5 billion per year.

The smart medications pillboxes [4] available on the market are continuously being upgraded owing to both the above-mentioned issue of deaths were caused by impropriety usage of medication. The PillDrill [5], for example: a smart medications pill box, will assist patients in the ease and comfort of storing and distribution of narcotics.

A patient could not, furthermore, know if the prescriptions he or she got are right. The broad spectrum of medicines used by patients with chronic disorders [6] specifically allows their detection a difficult job and misidentifying negligence-relevant medicines contributes to the risk of having the incorrect drug. False medication can lead to damaging interactions [7] or compensate the desired effects of both the medicines, leading to additional direct consequences, such as acute complications. This paper proposes a deep learning framework [8] for the identification of intelligent medicine, which will identify drugs and recall chronic conditions while taking certain medications. The United States in January 2016 A challenge contest for the creation of good performance algorithms and applications was declared by the National Library of Medicine to demonstrate how well customer photographs of pharmaceutical drugs fit the pills throughout his expert image set. This challenge was inspired by the desire for both healthcare insurance workers and the surrounding population to quickly recognize unknown pharmaceutical pills. Potential advantages of this capability include verifying the pill in conditions where paperwork and prescription have been divided, such as during a catastrophe or an accident, and confirming a pill whenever a new or generic approved medicine is shifting or the form and colour including its pill is changing for some other purpose. To solve this issue, this article proposes:

- Initially, FR-CNN extracts the features from the medicine pill images, which identifies the relationship between different types of images.
- Finally, the FR-CNN model is used to execute the multiclass medicine classification operation, which
is the final step.

- Comparing the proposed technique to state-of-the-art methods, the simulation results demonstrate that the new method outperforms the latter.

The following manuscript is contributed as follows: Section 2 deals with literature survey with drawbacks. Section 3 deals with the proposed method. Section 4 deals with results and discussions. Section 5 deals with conclusion and future scope.

### 2. Literature Survey

In [9], authors utilized machine learning descriptions of PillDrill’s product as well as its working are described mostly on web-site researcher. For patients including connectors to both the hub, access the programmed, link to the wireless internet network, and plan medication there are 4 phases. In [10], authors introduced the new platform mentions the medication that is needed. Audio visual knowledge is available with every medication. Pill packets must be scanned to follow the medications. It offers real-time confirmation by creating opportunities for revision of drug detail.

In [11], authors developed the machine learning based M’s high-tech opioid monitoring device. Brown reveals that it is easy to recall the specifics of medications across various categories of patients utilizing the smart prescription method. With the help of medication given by physicians, the author addressed the PillDrill technique [12] both for the elderly and the baby. With RFID they have to get specifics during taking tablets. This method used the wifi model and certain tags. In [13], authors aimed to understand the roles of healthcare & human interaction connected to ADRs (adverse drug reactions). Every application mentions the significance of the architecture and reporting for ADRs. The whole application often provides prediction information and also substance interaction avoidance utilizing multiple approaches and systems [14].

Many applications including the smart pharmacy box as alluded to in [15] are built to prevent the death from excessive medication ingestion. It facilitates the packaging, delivery and reminder of tablets by patient’s appropriate time. Some people take several pills [16], even patients with serious disorders. Since some patients have several tablets, other patients cannot remember if they took the tablets properly or not since various medications remain. Since this job is a little difficult, there is indeed a lot of risk that medications or medicines may be misidentified, which contributes to incorrect medicines. Failure to dose medication may contribute to severe and difficult offset.

In [17], authors developed an algorithm to identify prescription drugs smartly by accurately identifying and reminding patients to prevent this kind of issues. The risk of abuse of drugs is determined from first usage by the consumer, inevitably, before completion. In [18–20], authors presented many DL networks to detect deceases. Adverse events (AE), which are one of the main triggers of death and illness, are a big problem for health care [21]. For AE cases, there had been a recorded rise of 222% between 2006 and 2014 [13], according to the Food and Drug Administration (FDA). Indeed, since 1997, that FDA has registered volumes of all AE cases almost 5 times [13]. Owing to the manual
logging of specific incidents, pharmaceutical firms fail to manage elevated demand. In [22] authors introduced AE case logs have been expanded exponentially, but not a permanent approach. In this article, we speak about our work and results on even a solution towards medicinal monitoring. In order to classify serious vs. unwanted adverse case storey logs the approach discusses master learning strategies. In [23] authors discussed both conventional machine learning and profound education approaches during the creation of our technique. Their final model obtained an average F1-rate in AE event narratives of 95% as well as an MCC score around 0.80. In [24, 25], authors presented a CNN architectures to detect the diseases.

3. Proposed Method

The system described in this research is built on the TensorFlow framework and is based on an open-source module that combines FR-CNN as its neural network components. For training purposes, XML files containing drug information and the related drug images are translated into the "xml" format, and an appropriately modified "config" file is loaded, as shown in Figure 1. As seen in Figure 2, our deep-learning-based drug image detection strategy incorporates both the Faster R-CNN module. The deep-learning-based drug image identification mechanism used by the proposed system will be discussed in further detail in the following subsections of this section.

3.1. FR-CNN

The FR-CNN is shown in Figure 3, is indeed a CNN technique of target identification. Method maps first were drawn by layers [40] from Conv. The role maps are then moved to both the layer region proposal network (RPN), that produces frames across the potential object-containing regions. Instead, by region of interest (ROI) pooling sheet, the different performance framed areas were scaled to something like a fixed size and eventually transmitted to the classification to classify the entity in such framed areas. Conv Layers: FR-CNN includes coevolutionary layers, induction and pooling layers. Conv layers dimensions of both the original image shall be initially extended to $(M+2)^*(N+2)$ for all
convolutions in the FR-CNN Conv layers, accompanied by a M*N performance after 3x3 revolution. There are also no shifts throughout the matrix between both the input and output throughout the coevolutionary layers throughout the Conv layers, as can be seen in Figure 4. That kernel throughout the Conv layers of just about every pooling layer is 2 * 2 and the phase is 2. Those other settings halve the input measurements and minimize the equations of the M*N matrix, thus that it is made smaller to (M/2) * (N/2) through to the pooling layer). In brief, the convolutional and activation-function-layers in the whole Conv layer set may not adjust the input-size; only the pooling-layer adjusts the input-size by 1/2 of the output length and width. Therefore, Conv layers finally limit the M*N matrix towards (M/16)*(N/16). The functional maps created either by layers of Conv could therefore be related to the original image which is shown in the Figure 4. RPN Layers: An RPN utilizes a CNN to create regions of potential artefacts directly. The foreground & background were accomplished with SoftMax classification anchors (the detection objective is the foreground) as when the multiscale regional proposals with various aspect ratios could be created either by anchor mechanism as well as the frame regression. The RPN is indeed a completely linked coevolutionary network which can be used to train its frames throughout the created areas in order to forecast the border and range at
Figure 4. Feature extraction from convolution layer.

the same time as an item as shown in Figure 5. The Reg layer predicts the \((x, y, w, h)\) proposal co-ordinates referring to the proposition anchor. That layer of Class specifies if the idea is the front or rear. Anchors: The core of the \(3 \times 3\) convolution kernel seems to be the location of each anchor throughout the initial image because this is the center of every other anchor. Centered on all this, that original image is arranged with multiscale anchors with varying look ratios. That anchors therefore do not apply to the role maps of the Conv layers, but rather to the original image, as seen in the Figure6. Bounding Box Regression: In Figure 7, the yellow frame represents the goal object ground truth (GT), as well as the red frame represents its anchor removed. Because if the classifier recognizes the red frame as that of the goal object, the outcome of the detection would be deemed inaccurate if another red frame is not located accurately; the focus object is omitted from the frame. So, which is shown in Figure 7. we need to have a way of changing the red case to get the anchor close to both the GT.
ROI Pooling: The ROI pooling phase has two principal functions: (1) to coordinate an image item with the corresponding patch inside the feature chart and (2) to capture and transfer to something like a fully related layer the element corresponding to that map role patch. Each nominee region is equally divided into M x N blocks either by ROI pooling layer and has been maxed around each block. Proposals of varying scale on function maps are therefore transformed into standardized data and was sent as seen in the Figure 8 towards the next sheet.

Classification: The subclass to which any proposal belongs is now to be classified on the basis of both the fully-connected layer either layer including its SoftMax map area obtained with each proposal. For a more consistent location, the bounding box regression is being used to modify each anchor column as seen in Figure 9.
4. Results and Discussions
This work is concerned with the in-depth examination of the simulation findings, which is implemented by using MatlabR2021a. Furthermore, the proposed method’s performance is compared to that of the current approaches utilising a variety of qualitative metrics.

4.1. Dataset
As part of their Pill Image Recognition Challenge [18], the National Library of Medicine made available an image dataset (henceforth referred to as NLM PIR) with the purpose of assisting researchers in the development of high-quality algorithms and software that rate recognized prescription pill pictures. Fortunately, this dataset may also be used for picture classification, which is a bonus. Photographs from 1000 FDA-approved tablets were used to create the dataset, which was divided into two directories: IDC, which had 5000 consumer-quality images, and (secondary) DR, which contained 2000 reference images (double-sided 1000 pills). This work utilizes photographs from the DR directory, and nothing else. The DR directory covers a wide range of pills in a variety of sizes, shapes, and colors. The fact
that they may be categorized into three primary forms, namely capsule, oval, and round, is noteworthy. With a total of 1926 photos, these forms account for 96.3 percent of the DR directory. In this case, we eliminate the remaining 74 pill photos since there are just a few different forms available in the data set.

4.2. Subjective evaluation

![Figure 10](image1.png)

Figure 10 shows the classified outcomes using FR-CNN model. Figure 10 (a) shows the test pill images, Figure 10 (b) preprocessed outcome, Figure 10 (c) shows the segmented region, which contains the deep seismic features and Figure 10 (d) shows the classified medicines.

4.3. Objective Evaluation

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN [13]</td>
<td>61.11</td>
<td>61.13</td>
<td>68.54</td>
</tr>
<tr>
<td>ResNet50 [14]</td>
<td>81.37</td>
<td>85.00</td>
<td>71.76</td>
</tr>
<tr>
<td>Inception Net [17]</td>
<td>94.12</td>
<td>93.87</td>
<td>61.31</td>
</tr>
<tr>
<td>Proposed Classifier</td>
<td>93.12</td>
<td>95.54</td>
<td>95.76</td>
</tr>
</tbody>
</table>

Here, CNN [13], ResNet50 [14], and Inception Net [17] are examples of existing approaches, that are compared to the efficacy of the proposed methodology in Table 1. According to the results of the simulations, the proposed medical image classification technique outperformed all current methods for all metrics when compared to the existing approaches.

5. Conclusion

Chronic patients are plagued by a number of illnesses, with now 480 million older adults globally. Many medications are required and physiological roles degrade throughout the treatment of several chronic
diseases. That cognitive capacity to take the incorrect drug is decreased. As a consequence, older adults have been a harmful drug events high-risk category. Thus, this article successfully established an intelligent FR-CNN model for medicine pills recognition method, which solved the issue of existing methods. Initially, FR-CNN extracts the features from the medicine pill images, which identifies the relationship between different types of images. Finally, the FR-CNN model is used to execute the multiclass medicine classification operation, which is the final step. The simulation results shows that the prosper model resulted in superior performance as compared state of art approaches. This work can be extended with bio-optimization approaches for better feature selection.

References


