Doctor Handwritten Recognition and Alternate Medicine Recommendation using Deep Learning

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Abstract- Doctors' illegible handwriting in prescriptions cause trouble to both patients and pharmacists in many ways. Due to their handwriting pharmacists may not understand the medicine names and there is a chance that they may misunderstand the medicine names. If those misunderstood medicines are given to the patients rather than the prescribed ones, then that could cause them some other harm, there are chances that even that patients may die. Main problem here is that the prescription cannot be read. So, this proposed work would work as a solution for that. This proposed work can read the medical prescription when the image if the prescription is given character by character. Then along with that this proposed model could also recommend the alternate low-cost medicine. Many people do not know the actual alternate medicine they can cure their disease at a low cost. But this is not acceptable for all cases though. This will be very helpful for those people who are not able to afford the medicine cost. For medical prescription recognition a model which is a combination of AlexNet and SVM Classifier is used. AlexNet, which is a transfer learning model, is specifically used for feature extraction and SVM Classifier is used for classification. Through this process a remarkable accuracy of 98% has been achieved. This process starts with taking images as input and then the features extracted from the images with transfer learning model, then classification done using the SVM Classifier. That gives the recognized medicine name, using that name an alternate low-cost medicine will be given.

Keywords: AlexNet, Medical Prescription recognition, SVM classifier, Alternate low-cost medicine

I.INTRODUCTION

For any patient his medical record will be written by the doctors but unfortunately now-a-days the doctors are not writing in a clear way. This medical prescription [1][2] is something that is handwritten by the doctors when the patient visits, with some illness or injury. There are various reasons for them to write prescription in a scribbled manner. Now a days there are increasing numbers of patients whom they must attend so, as reason they are not taking long time to write the prescription in a clear manner instead, they are writing in a scribbled manner. That same prescription must be read by the pharmacists, they need to identify the names written by them and give the medicine to the patient.

But due to that scribbled prescription they are even facing issues to read the prescription. In our country there are some cases where the pharmacists have understood the medicine name in wrong way that is because there are many medicines with similar names. Doctors are writing only first half name of the medicine in a clear way, and they are not writing the second half of the medicine name in a clear way. That would lead to confusion for the pharmacists. There is s great chance for them to recognise the medicine name in a wrong manner.

Recognising medicine name in a wrong way is a great risk for the patient health. As a result of the mistake done by the pharmacists the patient health may largely deteriorate or sometimes that may be even threat to his/her life also i.e., they may die. According to the estimation done by the National Academy of Science [3][4] at least 1.5 million people are being killed or sickened every year due to incorrect reading of the medical prescription. The main reason for that is he error during the reading of the prescription. It is not possible to change the doctor to write the prescription in a clear way because they are attending many patients from day to day, so that would be a tiring task for them to write everything in a clear manner.

So, to reduce the errors in reading the prescription this handwriting recognition system would help a lot. Here for this the input can be the image of the prescription character by character and that identifies them. At the end that would combine all the characters and give the name together.

Transfer learning was chosen as a best option for this work because it would as those models are already well tuned on vast datasets. That would substantially cut down the time that is required to select a particular architecture and it would resolve the problem related to adjusting the weights of the neurons which is quite tiresome task. Also, the weights which ever are already assigned are not given randomly they are given in a very optimal way so that they would work for any kind of optimal cases as a result there would be less chances of failure. So, these pretrained models would reduce the time investment for many aspects.

According to the survey performed AlexNet is the Transfer learning model which would best fit the requirements that are to be satisfied. And then when it comes to Classification SVM Classifier [5] would perform better functioning. So, the proposed model is a combination of both the AlexNet and the SVM Classifier. One performs the task of feature extraction and the other performs the classification. In AlexNet only the convolution part is used for this.

After that the model has alternate medicine recommender in addition to the handwriting recogniser. The main task of the alternate medicine recommender is to identify the alternate medicine at low cost when compared to the medicine given in the prescription. If the prescribed medicine is the lowest cost medicine possible then that same name will be given back to the user.

Many people don't know what the alternate low-cost medicine is available in the market. And most of the people are not able to afford the medicine. Those who are unable to afford they are not using the medicine. So, for them this would help a lot. This will take the medicine name and then identifies the alternate low-cost medicine and gives to the user. It doesn't mean or to suggest everyone to use that medicine, but it gives the idea about the alternate medicine available at the low cost.

II. LITERATURE REVIEW

This section discusses various literatures on Medical Prescription Recognition. Most of the authors have proposed their works using various deep learning techniques and SVM.

In [2], to interpret the handwritten English prescriptions and convert them into the digital text they have used Convolutional Recurrent Neural Networks (CRNN) they have done this work using python language. When it comes to dataset, they have used dataset that contains 66 classes which includes various things such as alphanumeric characters, punctuations, and spaces. They have collected various handwritten prescriptions by the doctors, and they have used them to train their model. They have achieved almost 98% accuracy. For the better results they suggested about input handling.

Kamalanabanand et al [3], identified and perceived doctor's handwritten pharmaceutical names and returned a more understandable and coherent digital language using a medicine box and smartphone application based on Convolutional Neural Network (CNN). According to their observations they can achieve more accuracy when they have more accurate data.

To convert the multilingual textual symbols which are present on the paper into the machine processable text the usage of OCR was proposed in [5]. They have used various classifiers such as Linear-Support Vector Machine (LVM), k-Nearest Neighbours (KNN) and Multilayer Prescription Classifier. Their experiments show that they have achieved higher accuracy in case of English characters.

In [6], their work has used DCNN to identify the text in the handwritten prescription by doctor and it extracts readable text from that handwritten text. They have achieved 76% accuracy when they performed their experiment on almost 540 images.

The usage of neural network techniques such as CNN and BI-LSTM for predicting doctor's handwriting from medical prescriptions was proposed in [7]. The CTC loss function is used for normalization. This model builds on the IAM dataset. Image acquisition and data augmentation are used for image preprocessing. Furthermore, it is passed as input to 7 convolution layers of a 4 neural network.32 training epochs were used by the training model, which took six hours to complete training, and, on a graph, loss values are represented.

In [8], they have performed both Medical Formula Recognition and new Medical Formula creation. For this they have used One Class Learning and Support Vector Machine and they have achieved an accuracy of 82%.

Chinese character recognition techniques were concentrated more in [9]. In experiments, the Hidden Markov Model (HMM) performed better than "state-of-the-art methods" when used for data training.

S. Tabassum et al.,[11] advocates employing machine learning techniques to recognise doctors' handwriting and generate digital prescriptions using an online handwritten recognition system. A core "Handwritten Medical Term Corpus" dataset was created for the study using 17,431 data samples and 480 terms from 39 Bangladeshi doctors. The number of data samples is increased on the pre-processed images using a novel data augmentation method called SRP. The original and enhanced image data are then combined to create a sequence of line data. To achieve complete end-to-end recognition, bidirectional LSTM is applied to the sequential line data produced from the enhanced handwritten images. Without data expansion, the model had an accuracy of 73.4%, while with SRP data expansion, it had an accuracy of 89.5%.

P. S. Dhande et al. [14], they have used convex Hull Algorithm for feature extraction and SVM for classification. They achieved an accuracy of 95% for text-line segmentation and 92% for word line segmentation.

In [15], the authors have used the OCR techniques in order to transfer the human handwritten text into machine understandable text.

Analysis of previous works in being described in table 1.

Table-1: analysis of previous works.

R.No	Model	Accuracy
[2]	CNN + OCR	70%
[6]	DCNN	76%
[8]	One Class Learning + SVM	82%
[11]	Bi-LSTM+SRP+OCR	89.5%
[12]	CRNN	95%
[14]	Convex Hull Algorithm + SVM	95%

III. PROPOSED METHODOLOGY

This section explains the proposed methodology of this work . It starts with the discussion on the dataset used for the construction of this model. Then the main part of this work will be discussed i.e., the architecture of the model and the transfer learning models which are used in this proposed work. This section gives the brief description of the AlexNet Model and SVM Classifier. After that the alternate medicine recommender will also explained briefly. Let's start with discussion of the dataset first:

Dataset: As the exact dataset which would meet the requirements which were set initially so the dataset was manually created to meet those requirements. That dataset contains all the English alphabets. Along, with the English alphabets' numerals are also included because doctors usually mention numbers in their prescriptions. And each alphabet is again taken about 70 images. Each image is written different font size and different style. So, that the model could recognize as many as possible types of handwritings. The dataset looks like the following figure 1. The below figure is the repository image which shows how the data has been created. Each individual character and numeral have a separate folder for each. Each folder contains the images related to that label in different variations.

Fig-1: Dataset image

The proposed methodology of this proposed work involves the usage of AlexNet for feature extraction and then SVM Classifier for classification. The main part of this proposed work is feature extraction which is done using Transfer learning. This comes under transfer learning because AlexNet architecture is a pre-defined model which is trained in large datasets, it must be just configured according to the adjustments and requirements.

As mentioned above the dataset which is used in this work was manually created so there is always a chance of having some noise or impurities in it. If the model is fed with the images having noise the accuracy could alter. Also, during the process of creating the dataset, the images are formed with different sizes. But all of them must be resized to 227*227. Images must be resized to that size because that is the input size of the AlexNet input layer.

Then the pre-processed dataset is fed to the model i.e., AlexNet. From AlexNet only the convolution part is taken for the construction. In general, the AlexNet architecture contains 8 layers, of which 5 layers are convolution layers along with three pooling layers which are max pooling. Then three fully connected neural network layers are used. From all these layers the beginning 5 layers are used for feature extraction and the remaining three fully connected neural network layers are used for classification. But from the whole 8 layers, only the first five convolution layers along with the pooling layers are taken not consideration. The main purpose of using this AlexNet is for feature extraction which can be completed just by using the convolutional layers so neural network's part is completely avoided.

Then the features extracted are used for classifying. The classifier which has been used is Support Vector Machine Classifier. The features are sent to the classifier, the model gets adapted according to the features.

After that, the model is fed with the test and validation data for verifying the accuracy of the model. Then according to the accuracy that are obtained, the model must be changed so that the results could be better.

Figure 2 shows the architecture of the proposed work. Figure clearly shows the input size of the model, and it shows about how the size is getting reduced. The output from each layer is considered as a feature map. The feature map size is constantly reduced because of the pooling layers. They reduce the size of the feature map to reduce the computational costs.

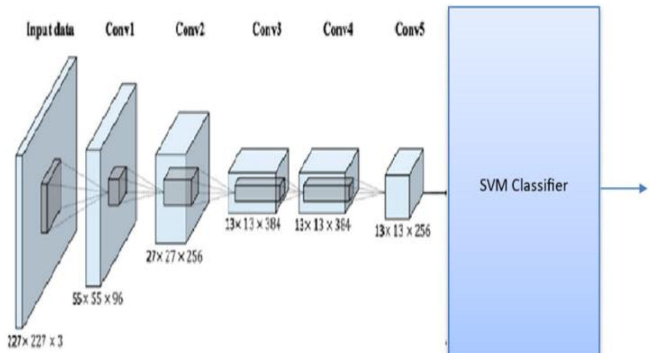

Fig-2: Model architecture of the proposed work

All the process mentioned above which is a combination of the AlexNet and SVM classifier was only for recognising the medicine which was prescribed by the doctor. But the proposed work has the later part of it which was the alternate low-cost medicine recommendation.

Then the alternate low-cost medicine recommendation comes into the picture. The alternate low-cost medicine recommendation is done using the predefined API. The API identifies the low-cost alternate medicine and produces the result. Here the validation is not necessary as the results are produced by API.

The proposed model workflow is shown in the figure 3. That represents the whole process in step-by-step format starting from data collection to the final output that is recommendation of alternate low-cost medicine.

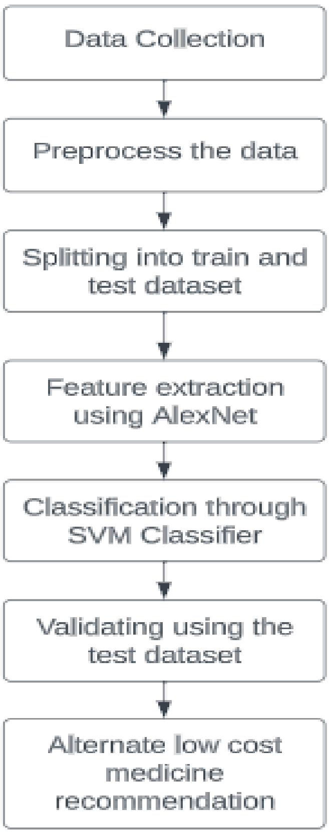

Fig-3: Flow diagram of the proposed work

IV. RESULTS AND DISCUSSIONS

The input of the proposed model would be the images of the prescription character by character. Then model will first identify the features from the images and SVM classifier will classify and identify the character. Then that characters will be used to identify the alternate medicine.

The handwritten recognition system was able to correct recognize the input and was able to provide accurate alternative. The output will be of two parts first the medicine identified output will be given as output. Figure 4 shows the medicine name which is recognised by the model.

```
# Print the predicted class names
med = "".join(predicted_classes)
print("Medicine: ",med)
```

```
Medicine:  DOLO650
```

Fig-4: Model prediction screen first part name recognition

Then the second part is the alternate low-cost medicine recommender. The medicine recognition output and the alternate medicine names are given as two separate parts. The alternate low-cost medicine recommended by the model for medicine Dolo650 is shown in figure 5.

```
print(response['choices'][0]['text'],'\n')
```

```
Ibuprofen
```

Fig-5: Model prediction for alternate medicine recommendation

The alternate medicine recommendation system provided relevant recommendations based on the recognized letters, enabling users to explore alternative medicine options associated with specific letters. However, it is important to note that the accuracy of the handwritten recognition system and the effectiveness of the alternate medicine recommendations heavily rely on the quality and diversity of the training dataset. Further enhancements and refinements can be made to improve the system's accuracy and expand the range of alternative medicine recommendations. The confusion matrix is shown by figure 6:

```
Confusion Matrix:
[[ 9  0  0 ...  0  0  0]
 [ 0 11  0 ...  0  0  0]
 [ 0  0 15 ...  0  0  0]
 ...
 [ 0  0  0 ... 12  0  0]
 [ 0  0  0 ...  0 14  0]
 [ 0  0  0 ...  0  0 17]]
```

Fig-6: Confusion matrix of the proposed work

Accuracy: Accuracy is how close a given set of measurements (observations or readings) are to their true value.
Accuracy = (TP+TN)/ (TP+TN+FP+FN)
The accuracy of this work is: 98%

Precision: Precision is defined as the ratio of correctly classified positive samples (True Positive) to a total number of classified positive samples (either correctly or incorrectly).

The precision of this work is: 98%

Recall: The recall is calculated as the ratio between the number of Positive samples correctly classified as Positive to the total number of Positive samples. The recall measures the model's ability to detect positive samples. The higher the recall, the more positive samples detected.
Recall= TP/(FN+TP)
Recall for this work: 98%

F1 Score: The F 1 score is the harmonic mean of the precision and recall. It thus symmetrically represents both precision and recall in one metric.
F1 score= 2*(precision * recall)/(precision + recall)

F1 score of this model is: 98%

Accuracy, precision, Recall and F1 score all are performance measures of the model.

In the above formulas various terms are used they are:
TP: True Positive
FP: False Positive
TN: True Negative.
FN: False Negative

The below table gives a summary of the comparison the proposed model with the previous existing models. The previous existing models are also based on deep learning techniques but each one of them has their own way of using various algorithms. Now the table compares the accuracy achieved by the existing model with the proposed model accuracy. Below table 2 shows the comparison of the proposed model with the existing models.

Table-2: Comparison of proposed work with existing works

R. No	Model	Accuracy
[2]	CNN+OCR	70%
[6]	DCNN	76%
[8]	One Class Learning + SVM	82%
[11]	Bi-LSTM+SRP+OCR	89.5%
[12]	CRNN	95%
[14]	Convex Hull Algorithm + SVM	95%
proposed	AlexNet+ SVM Classifier	98%

V. CONCLUSION & FUTURE SCOPE

This work mainly focused on medical prescription recognition using the AlexNet architecture for feature extraction and an SVM classifier. The goal was to develop a system that could accurately interpret prescriptions and provide low-cost alternate medicine recommendations. Through these experiments, it was observed that the combination of AlexNet and SVM yielded promising results in recognizing medical prescriptions. The deep learning features extracted by AlexNet effectively captured relevant patterns and characteristics of the prescriptions, while the SVM classifier provided robust classification performance.

This model is giving accuracy around 98%. This accuracy is tested for the validation dataset. This data has not been seen by the model during the training phase.

The accuracy could be increased even more if the dataset size gets increased. Furthermore, there is an intention to expand the dataset's capability to identify medicine names as complete words rather than just individual terms.

REFERENCES

1. William C. Shiel Jr. (accessed month: July, 2023) https://www.medicinenet.com/prescription/definition.htm "Medical Definition of Prescription".
2. E. Hassan, H. Tarek, M. Hazem, S. Bahnacy, L. Shaheen and W. H. Elashmwai, "Medical Prescription Recognition using Machine Learning," 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), NV, USA, 2021, pp. 0973-0979, doi: 10.1109/CCWC51732.2021.9376141.
3. Kamalanabanand E. Gopinathand M Premkumar. https://www.sciencepubco.com/index.php/ijet/article/view/18785 "Medicine Box: Doctor's Prescription Recognition Using Deep Machine Learning". In: (2018).
4. H. Brits, A. Botha, L. Niksch, R. Terblanche, K. Venter G. Joubert. ´https://www.tandfonline.com/doi/full/10.1080/20786190.2016.1254932 "Illegible handwriting and other prescription errors on prescriptions at National District Hospital, Bloemfontein".
5. Kumar, M., Jindal, S.R. A Study on Recognition of Pre-segmented Handwritten Multi-lingual Characters. *Arch Computat Methods Eng* **27**, 577–589 (2020). https://doi.org/10.1007/s11831-019-09332-0
6. L. J. Fajardo et al., "Doctor's Cursive Handwriting Recognition System Using Deep Learning," 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), Laoag, Philippines, 2019, pp. 1-6, doi: 10.1109/HNICEM48295.2019.9073521.
7. T. Jain, R. Sharma and R. Malhotra, "Handwriting Recognition for Medical Prescriptions using a CNN-Bi-LSTM Model," 2021 6th International Conference for Convergence in Technology (I2CT), Maharashtra, India, 2021, pp. 1-4, doi: 10.1109/I2CT51068.2021.9418153.
8. O. Kawi, K. Clawson, P. Dunn, D. Knight, J. Hodgson and Y. Peng, "Medical Formulation Recognition (MFR) using Deep Feature Learning and One Class SVM," 2020 International Joint Conference on Neural Networks (IJCNN), Glasgow, UK, 2020, pp. 1-7, doi: 10.1109/IJCNN48605.2020.9206955.
9. L. Xu, Y. Wang, X. Li and M. Pan, "Recognition of Handwritten Chinese Characters Based on Concept Learning," in IEEE Access, vol. 7, pp. 102039-102053, 2019, doi: 10.1109/ACCESS.2019.2930799.
10. P. Wu, F. Wang and J. Liu, "An Integrated Multi-Classifier Method for Handwritten Chinese Medicine Prescription Recognition," 2018 IEEE 9th International Conference on Software Engineering and Service Science (ICSESS), Beijing, China, 2018, pp. 1-4, doi: 10.1109/ICSESS.2018.8663789.
11. S. Tabassum et al., Recognition of Doctors' Cursive Handwritten Medical Words by using Bidirectional LSTM and SRP Data Augmentation,In 2021 IEEE Technology & Engineering Management Conference - Europe (TEMSCON-EUR), Dubrovnik, Croatia, 2021, pp. 1-6, doi: 10.1109/TEMSCON-EUR52034.2021.9488622.
12. R. Achkar, K. Ghayad, R. Haidar, S. Saleh and R. Al Hajj, "Medical Handwritten Prescription Recognition Using CRNN," 2019 International Conference on Computer, Information and Telecommunication Systems (CITS),

Beijing, China, 2019, pp. 1-5, doi: 10.1109/CITS.2019.8862004.

13. U. Shaw, Tania, R. Mamgai and I. Malhotra, ”Medical Handwritten Prescription Recognition and Information Retrieval using Neural Network,” 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), Solan, India, 2021, pp. 46-50, doi: 10.1109/ISPCC53510.2021.9609390.
14. P. S. Dhande and R. Kharat, ”Character Recognition for Cursive English Handwriting to Recognize Medicine Name from Doctor’s Prescription,” International Conference on Computing, Communication, Control and Automation (ICCUBEA), Pune, India, 2017 2017 , pp. 1-5, doi: 10.1109/ICCUBEA.2017.8463842.
15. S. Butala, A. Lad, H. Chheda, M. Bhat and A. Nimkar, ”Natural Language Parser for Physician’s Handwritten Prescription,” 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India, 2020, pp. 1-7, doi: 10.1109/icETITE47903.2020.325.