Chatbot based Crime Registration and Crime Awareness System using a custom Named Entity Recognition Model for Extracting Information from Complaints

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Abstract - *In this paper, we present a chatbot for crime awareness and crime registration. Our chat-bot uses a combination of classification and generative models. Text is generated by using encoder-decoder attention mechanism architecture. It is incorporated with features like spam classification of SMS and emails to re-duce cybercrimes. It has a complaint registration system that allows users to file complaints, a custom named entity recognition model is used to extract structured information like location, time, and crime type from unstructured complaints, this would allow the authorities to effectively and efficiently comprehend com-plaints. We strive to provide efficient and user-friendly methods for registering complaints using these techniques and informing individuals about the judicial system. Thus, we aspire to apply Natural Language Processing (NLP) for social good.*

Key Words: Natural Language Processing, Named Entity Recognition, Text Generation, seq2seq model, Chatbots, Crime Registration.

1. INTRODUCTION

Crime has been a grim and strong undercurrent of human culture throughout history. Activities like murder, thefts and attacks happening frequently are indications of an unsafe society. These kinds of activities have been happening since a very long time. Assassination of famous political leaders like Julius Caesar, John F Kennedy etc. have changed many outcomes in history. In medieval times many activities happened like poaching, killing, assassinations, wars between colonies. Until the late1800's the word 'crime' as we know now, wasn't even pa art of the vocabulary of common people. The invention of firearms led to rapid rise of many criminal activities and gun violence. Seeing this rise many countries started to keep many rules and laws for monitoring and controlling criminal activities. In India, the Indian penal code [1] was enacted on the 6th of October 1860. Later several other acts like 'The Indian evidence act' [2], 'The code of criminal procedure' [3] came up which enforced several laws and punishments and contributed in controlling different types of crimes to create a safer society. The challenge is to make everyone aware of these crimes, allows everyone to understand the judicial system. Some laws are not known to most people like exceptions (in which a person is forgiven of a crime), witness protection and cyber crime related laws. The rise in technology saw many cyber crimes like phishing, identity theft scams and online harassment [4;5]. It is of prime importance that every citizen knows about these laws and be prepared. The documents like the 'Indian penal code' [1] are very descriptive and hard to understand. The crime registration system too is not effective in many places like the rural areas. There are many instances where response time for lodging FIR is very high.[6] In recent times, cybercrimes are one of the most seen criminal offenses; most of the cybercrimes are based on a fraudulent email or SMS. Spam messages have always been a problem not only because of its fraudulent potential, but because of its sheer magnitude. It is estimated that more than 300 billion emails are sent daily, 80 to 85% of this mass email traffic is spam [5] which is troublesome as it restricts the flow of legitimate internet traffic around the world. We have added a spam detection feature in the chatbot where the users can copy paste an email/SMS they suspect to be spam, the message is checked using a binary classification model and the chatbot informs the user if it is a spam or ham (i.e. not spam). This would help users to avoid being the victims of cyber crimes like phishing, identity theft and online credential. In response to the above challenges we pro-pose Cowboy, an efficient and user-friendly Chatbot based crime registration and crime awareness sys-tem. Chatbots are the latest instalments in industries to improve human-machine interaction, reducing both cost and human efforts in solving queries of the customers. From usability perspective, chat-bots are very easy to use and interact with. Offer many features enabling them to be used in many applications. Cowboy is built using algorithms for classification of the queries related to crimes asked by the user and respond accordingly. The user can also register a complaint using this Chatbot where the complaint is sent to authorities via an email. Since, there is no specific format for registering a complaint, they tend to be very descriptive and unstructured. It's very hard and time consuming to understand the important information which can be one of the reasons for the response time to be more. To solve these problems and make it easy for a citizen to not only register a complaint but also understand laws related to certain incidents, we built a custom named-entity recognition model which will extract important structured information from a complaint like time of incident, type of crime and give appropriate response.

2. LITERATURE REVIEW

Development of chatbots started in the 1960s when the first chatbot - Eliza was developed by MIT professor Joseph Weizenbaum [7]. Eliza was capable of asking open questions and answering them imitating the role of a psychotherapist. Another popular chatbot called Parry was developed in 1972 by a psychiatrist at Stanford's Psychiatry Department [8]. This chatbot was completely opposite from Eliza as it behaved as a patient with schizophrenia. Many other chatbots like Dr Sabaitso (acronymfrom 'Sound Blaster Artificial Intelligent Text to Speech Operator'), Story telling chatbots like Racter and [9;10] were developed in the late 20th century for research, psychotherapy and other applications, although these chatbots mimicked human conversation they had only a limited knowledge about the domain [11;12]. Hence chatbots were not very popular in those days. Social media websites like Facebook and Messenger increased the popularity of chatting with people via the internet. Many developments in the area of natural language processing enabled developers to build chatbots. Later many architectures were developed for building chatbots such as: Elizabeth [13] and ALICE (acronym from 'Artificial Linguistic Internet Computer Entity') was developed by [14]. In 2009 a Chinese company Wechat created a chatbot which instantly became very popular. Several other social media websites developed many chatbots in 2010s. Many domains like restaurants, banking, medical, customer feedback and transport began to use chatbots to increase their services. One of the best examples of chatbots in use can be seen in KLM - a Dutch airline. In 2006 they developed a chatbot which successfully responded to10% of the queries [15]. This chatbot is still underdevelopment with many new additional features like flight booking and ordering food to meet the demands of their passengers. Today, this Chatbot is responsible for answering more than 1 million customer queries. Most of these chatbots usually are useful for a specific application. However, they were not contextual and their responses are usually pre-programmed. Hence the chatbots generated the same responses repeatedly which is not very human-like. Since Noah Chomsky one of the first linguists started syntactic theories in the twelfth century and revolutionised the field of theoretical linguistics[16], many developments have been done in natural language processing and computer linguists. NLP enables machines to analyse text similar to humans. Many researches have been done in this field such as:

- POS tagging: which gives machines the ability to understand the grammar of the sentences.[17]
- Text summarization: It is a method of creating a brief and insightful description of text from various text resources
- Stemming: A process that maps words to its base forms. It can be classified into two types- dictionary based stemming and Porter style stemming[18].

For this chatbot Porter stemming is used. Another remarkable technology in NLP is named-entity recognition (NER). NER is a process of identifying different words of interest from a sentence such as names, places, dates, times and prices. This can be used for many specific applications in different areas like using NER based models to classify news stories [19]. MITA (Metlife's Intelligent Text Analyzer) is a system which extracts information from life insurance applications [20].NER models can be specifically designed for extracting some specific entities for different applications. This process is known as custom named entity recognition. Many frameworks are available which allow developers to train a custom named entity recognition. One such tool is SpaCy1. SpaCy is a powerful NLP framework that uses transformers based pipelines. It is one of the most accurate framework for NLP applications. In 2015 are search conducted by Emory University and Yahoo! Labs showed that SpaCy offered the fastest syntactic parser in the world [21;22]. Med7 is a NER model for extracting information from electronic health records [23]. Custom NER can also be used for parsing resumes [24]. These NER models in different applications help save a lot of time and effort of reading textual data manually. Many more domains can incorporate this technology. We have reviewed the vast applications of chatbots and named entity recognition and we have witnessed how using these in different domains could be very beneficial. In this work, our focus is to build a chat-bot assisted with a NER model for improving the crime registration system and also help in increasing crime awareness. We thus wish to contribute in accomplishing United Nations sustainable goal 16: Promote just, peaceful and inclusive societies [25].

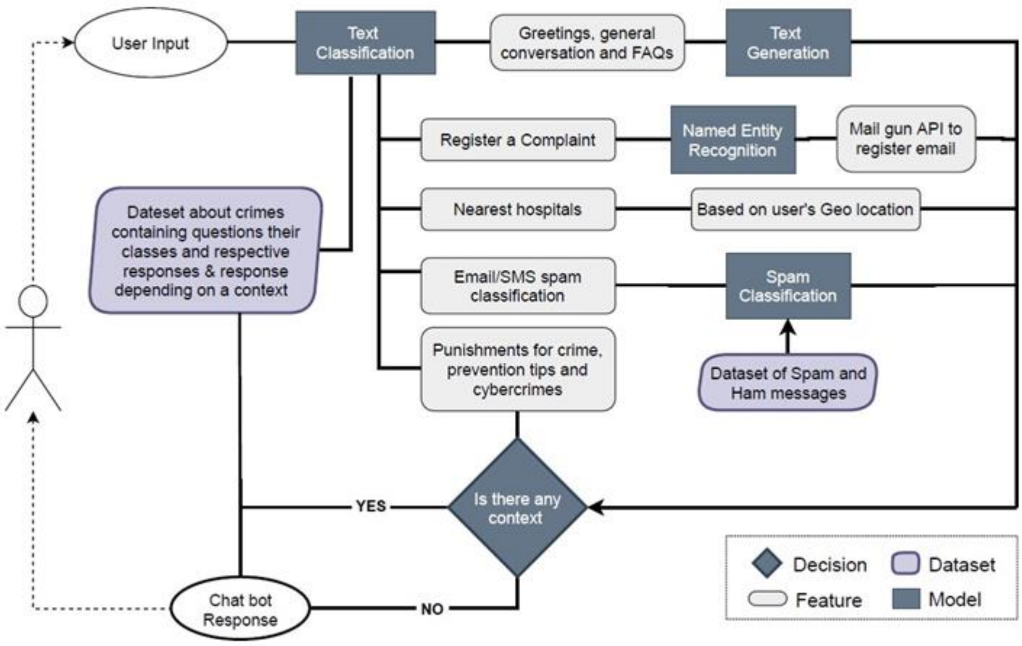
3. METHODOLOGY

This chatbot uses numerous machine learning algorithms for implementing different features. Figure 1 shows the complete architecture of the chat-bot briefly showing the functionality and different features offered. In this section we will see the working of the chatbot in detail

3.1 Classification model

A deep neural network model is built for classification of input text into following categories:

- Complaint Registration



- Nearest Hospitals
- Spam Classification
- More than 100 topics related to punishments of different crimes, crime prevention tips and cyber crimes. Examples: tips for safely doing online transactions, murder, thefts, phishing etc.

This is the initial step of the chatbot, if the DNN model classifies the user input as any of the topics related to crimes respective response is given by the chatbot. If the user input belongs to other classes it uses different features/models which are explained in following sections.

Dataset: The dataset is a json file created manually. It contains more than 400 questions and responses on different laws, preventive measures and crime related information as per Indian Penal Code. For testing a dataset was created consisting of 200 different possible messages from users.

Context: One of the limitations of chatbots is that they are unable to remember context of a conversation, when two people interact with each other both are aware of the topic of conversation, which is not seen human-Chatbot interaction. This Chatbot is not purely contextual but for some topics the bot understands the topic and the conversation are specific to that topic until the requirement is over. Consider the following conversation by cowboy with a user.

User: I want to register a complaint
Cowboy: For registering complaint type "yes" to continue.
User: yes
Cowboy: Enter your name, location and details of the complaint
User: Some people approached me from behind in 200 block of State St. threatened and demanded money. I gave away my wallet then they fled area on foot.
Cowboy: Your complaint was registered successfully

As seen in the above example the chatbot continues to talk about complaint registration after registering the complaint it again returns to normal. Figure 2 is a sunburst chart showing the context in the chatbot.

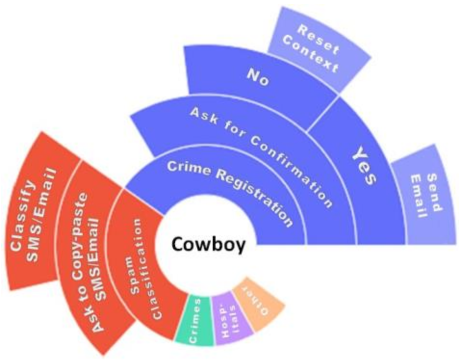


Fig -2: Context in the Chatbot

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3.2 Text generation

We wanted to make the chatbot more open domain by implementing a model that would generate text rather than having predefined responses. For responses related to crimes punishments/laws we proceeding with pre-defined responses as the answers are very complex to be easily generated. We are using text generation to answer simple questions, general conversation and FAQs about crime where the response is limited to 1-2 sentences.

Dataset: Large corpus containing questions and answers about FAQ's in crimes, cybercrimes and preventive measures also general conversations like greetings, chit-chat etc. For generation we could not include In this section we have explained different deep learning models we tried to implement for text generation, their limitations and the final model we selected for this application.

RNN (Recurrent neural network): When we start to speak words we usually frame sentences and understand words after remembering the previous words in the sentence. This is a memory technique by which humans learn to speak. Since our application imitates human conversation it is ideal to use a neural network which works in a similar way. RNNs can be used to achieve this. RNNs are a special type of neural networks where the output of the previous timestep is given as input of the current timestep. However while working for large sequences like large English sentences, the RNN model fails to predict the next sequence of words accurately. This problem is known as long term dependency [26].

LSTM (Long Short term memory): LSTM was designed to avoid the long term dependency problem seen in RNNs. The main difference between the RNN and LSTM is that in LSTM the repeating module has four neural networks interacting in a unique way whereas in RNN there was only one layer (as seen in figure 3). This combination of layers are capable of storing more information.

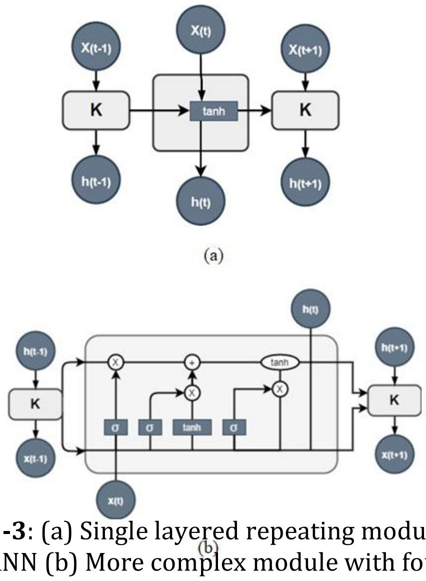

Fig -3: (a) Single layered repeating module in RNN (b) More complex module with four interacting layers in LSTM

Encoder-Decoder Model: For using LSTM the input and the output should have the same number of sequences, this limitation does not allow us to use it for our chatbot. For example if the user input is "hi there" which is two sequences the desired output should be "Hi how are you" which is four sequences. Hence, the LSTM model wouldn't work here because of variable length input and output. In many applications related to natural language processing like machine translation, text summarisation, image captioning etc. the length of input and output sequences vary, to implement these encoder decoder LSTM can be used.

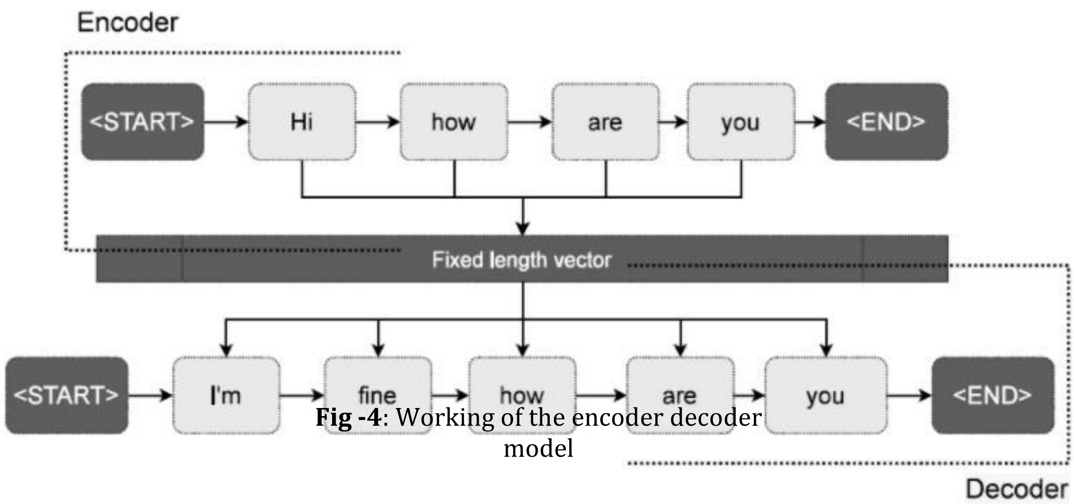

Fig -4: Working of the encoder decoder model

The idea is to use 2 RNNs that function together one is the encoder which reads the variable length input sequence and maps it into a fixed length vector other is the decoder which decodes the fixed length sequence into variable length predicted output.

Dataset: The dataset contains sentences of questions and answers the sentence is preprocessed 'Start' and 'End' tags added to the beginning and end of the sentence respectively, this is to ensure that the seq2seq model knows when to start and stop generating text. The preprocessed text is converted into vectors by performing one hot encoding. Our encoder model includes an input layer that specifies a matrix for storing the one-hot vectors and an LSTM layer with some hidden states. The configuration of the decoder model is exactly the same as that of the encoder, except the state data is transferred along with the decoder inputs. Here, we are using rmsprop as an optimizer and categorical cross-entropy as our loss function, working of the model (is shown in figure 4.)

3.3 Complaint registration

To enable the chatbot to register a complaint we are using mailgun API, an open domain tool for sending emails. For this research we are using the free version, to implement this system in real life we can host it on a domain and send complaints via email to police authorities.

3.4 Named Entity Recognition

There is no specific format for lodging a com-plaint, thus description of the complaint can change from person to person i.e. it is unstructured. The complaint may be registered with multiple users in a different way. One user can register a complaint so plainly and explicitly, while another user may be more descriptive in posing the same com-plaint. Problem arises when a certain police officer/respective authority wants to take action on a complaint, they have to read through the whole paragraph at least once to understand the useful information. This is inefficient and time consuming. The specific problem we focus on is extracting structured information from unstructured com-plaints registered by a user. We want to extract key entities such as the date of incident, type of crime, victim, location of crime etc. This helps in indexing complaints for scientific (future research on different factors causing crimes) and investigative purposes. To implement this in the chatbot we built a custom NER model using SpaCy python library which provides industrial-strength natural language processing. SpaCy has built-in pipeline components like parser, NER and textcat. For any NLP task using SpaCy first tokenizer is applied and a series of pipelines are applied depending on the application. However for this application NER pipeline is used.

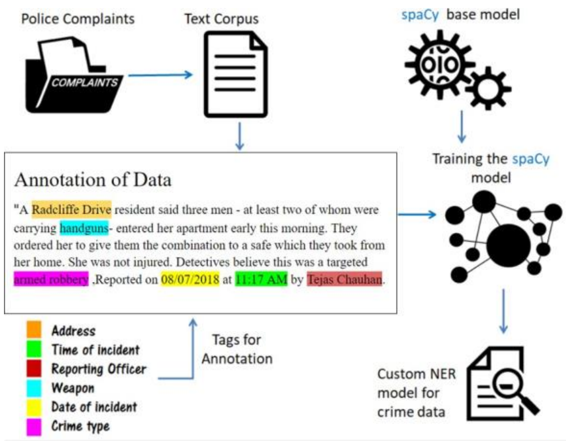

Fig -5: Named entity recognition model

Dataset: List of crime incidents reported in the city of Madison [28]. Several features. Some of the data is annotated for the NER model to understand the entities. Table 1 shows the entities in the test data for evaluating NER model.

Entity	Count
Address	97
Date	46
Crime	102
Reported date	59
Reported time	63
Reported by	10
Weapon	37
Total Entities	406

Table -1: Entities in test dataset

Using the annotated dataset we initially trained the NER pipeline of the base model of SpaCy after training the NER model would identify crime related entities (as shown in figure 5). When a user registers a complaint the chatbot uses this model and sends the complaint along with key entities through email.

3.5 Spam Classification

Dataset: SMS messages in English of 5,574 messages, tagged according being ham (legitimate) or spam [29]. Support vector machines (SVM) is an algorithm that identifies the best boundary of decision be-tween vectors belonging to a given group (or category) and non-belonging vectors. It can be ex-tended to all types of vectors that encode data of some kind. For applying SVM different kernels are required each classification problem is different and the work of the kernel relies on what the data looks like we are using linear kernel. To achieve text classification texts need to be translated into vectors to utilize the strength of SVM text classification. Using this algorithm we were able implement text classification for the chatbot.

3.6 Nearest hospitals

Cowboy can also be used for instantly getting list of nearest hospitals in case of any emergencies.

Dataset: List of all the hospitals in India with their geocodes.

Based on the geocode of the user's location, The chatbot suggests the top five nearest hospitals w.r.t their geocode in the dataset.

4. RESULTS

4.1 Spam Classification

Evaluation is a crucial part in developing any ma-chine learning model as it shows the performance of the model giving an opportunity to improve them. Precision is determined as the amount of true positives separated by the overall number of true positives and false positives in an imbalanced classification problem of different classes. Recall is a statistic that out of all positive predictions that may have been made quantifies the number of accurate positive predictions made.

$$\text{Recall} = \frac{\text{True positives}}{\text{Number of positives}} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Precision} = \frac{\text{True positives}}{\text{Number of predicted positive}} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Both precision and recall show how a modelperforms to to get a balance between the precisionand recall a metric called f1score is used which iscalculated by the following formula:-

$$F_1 = \left(\frac{\text{recall}^{-1} + \text{precision}^{-1}}{2}\right)^{-1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}.$$

4.2 DNN Model Accuracy

The initial task of the chatbot is to classify theuser input into different categories after which thechatbot decides response and which model is used.The classification model uses DNN which was ableto classify 92.6% of the messages accurately.

4.3 NER Evaluation

Graph 1 shows the performance of the named entity recognition.

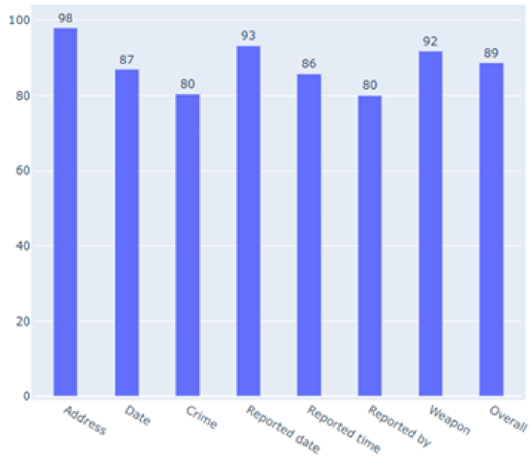

Chart -1: Entity wise accuracy of NER model

The named entity recognition performs well in identifying addresses, time of incident and weapons for example if the complaint is

> "Upon arrival officers learned that the victim had been stabbed by a **knife**"

The model will identify the weapon as a knife which is correct. In case the complaint is

> "Upon arrival officers learned that the victim had been stabbed by a **unknown suspect**"

Here there is a possibility that the model miss classifies "unknown suspect" as a weapon, but the model does not do that and understands the difference. Hence the model is good enough to identify weapons, address and time of incident even in tricky situations as seen in above complaint. However it under performs in identifying the crime types because some crime types like carrying drugs, damaging public property are very rare in the dataset of the complaints and the model does not identify the crime type or misclassifies it. For example:-

> "A **strong-armed robber** pushed his way behind the sales counter at the Spirit gas station and **demanded money**"

In the above complaint the model identifies both "demanded money" and "strong armed robber" as the crime type while "demanded money" is correct "strong armed robber" is incorrect crime type. "strong armed robber" is very similar in composition of words with "strong armed robbery" and hence the model incorrectly predicts it as a crime 'type'. (As seen in the figure 6) the NER model gives decent results in identifying all the entities.

4.4 Spam classification

Performance of spam classification model (is shown in table 2)

Class	Precision	Recall	F1 Score
Ham	0.971	0.99	0.98
Spam	0.936	0.80	0.86

Table -2: Evaluation of Spam detection model

5 ETHICAL CONSIDERATIONS

The chatbot is aimed towards solving social problems. Following are the different ethical considerations required to ensure safe usage of thischatbot.

5.1 Use Cases

1. People living in rural areas need to be made aware of different crimes, punishments and preventive measures.
2. A person is new to the internet and wants to be aware of cyber crimes or they want to get tips to use the internet safely.
3. People want to register a complaint to the po- lice
4. Someone witnessed a fight and a victim is severely injured and they need to find the near- est hospital.
5. An engineering graduate gets an email which is offering a job with a very high package from an unknown company and they want to know if it is spam or legitimate.
6. A newly wedded couple shift to a city with a high crime rate and they need to know how to prevent house thefts.

5.2 Failure modes

There is a slight chance that spam classification model misclassifes spam message as a genuine (There are many spammers who adapt to spam detection systems). In this case might user might find themself in a phishing scam.

5.3 Misuse potential

There is a potential that this chatbot can be misused to send fake complaints (Complaints which didn't occur but someone sends it). This would in- crease the difficulty for the authorities to address complaints.

6. CONCLUSION

In this work, we present a chatbot which is capable of helping citizens in any crime related queries. Currently the chatbot is built to give information only about criminal laws of the Indian subcontinent. This chatbot can be used for crime aware-ness, crime registration where NER model used to identify entities of complaints good accuracy of 0.87, finding nearest hospitals, spam detection with decent F1 Score of 0.98 (Ham) and 0.86 (Spam).This approach of building a custom named entity recognition model could be further applied to many other domains like newsletters, resume and medical applications. In future, we plan to improve the performance of the NER model to identify different entities, include more entities to gain much more deeper insights from the complaints registered and experiment on how the performance will change. Information of criminal laws of other countries can be added to the chatbot. Currently, the chatbot only partially uses generative models. This is to avoid incorrect responses for complicated requests such as criminal laws responses. These responses are predefined. As a next step we plan to train the seq2seq model for every response. Our chatbot presents a wholistic approach towards tackling the problem of crime by enabling crime registration, creating awareness about crimes, identifying nearest hospitals and contributing in creating a safer society for all.

REFERENCES

[1] IPC. British legislative assembly now succeeded by parliament of India, "Indian penal code," 1860.

[2] Indian evidence act, 1875

[3] The code of criminal procedure,1973

[4] G. Aggarwal, "General awareness on cyber crime.," International Journal of Advanced Research in Com- puter Science and Software Engineering. Vol 5, Issue 8, vol. 5, 2015.

[5] M. Alazab and R. Broadhurst, "Spam and criminal activity," Trends and Issues in Crime and Criminal Justice, vol. ISSN 1836-2206, pp. 1–20, 12 2016.

[6] D. R. Yadav, "First information report and delay in registration of a case: A study of judicial trends," 03 2012.

[7] J. Weizenbaum, "Eliza—a computer program for the study of natural language communication between man and machine," Commun. ACM, vol. 9, pp. 36– 45, 1966.

[8] S. G u¨ven, "Dialogues with colorful "personalities" of early ai.," p. 161–169, 1995.

[9] C. Curry and J. O'Shea, "The implementation of a storytelling chatbot," 06 2011.

[10] W. Chamberlain, The policeman's beard is half constructed. Warner Books. 1984.

[11] H.-Y. Shum, X. He, and D. Li, "From eliza to xi- aoice: Challenges and opportunities with social chat- bots," Frontiers of Information Technology and Elec- tronic Engineering, vol. 19, 01 2018.

[12] T. Zem cˇ´ık, "A brief history of chatbots," DEStech Transactions on Computer Science and Engineering, 10 2019.

[13] B. Shawar and E. Atwell, "A comparison be- tween alice and elizabeth chatbot systems," Univer- sity of Leeds, School of Computing research report 2002.19, 02 2004.

[14] R. Wallace, The anatomy of A.L.I.C.E, pp. 181– 210. 01 2009.

[15] G. Caffyn, "How klm uses artificial intelligence in customer service," 2016.

[16] N. Chomsky, Aspects of the Theory of Syntax.1965.

[17] L. M a`rquez, L. Padro´, and H. Rodr´ıguez, "A ma- chine learning approach to pos tagging," Machine Learning, vol. 39, pp. 59–91, 04 2000.

[18] M. Porter, "An algorithm for suffix stripping," Pro- gram, vol. 40, pp. 211–218, 1980.

[19] Y. Gui, Z. Gao, R. Li, and X. Yang, "Hierarchical text classification for news articles based-on named entities," in Advanced Data Mining and Applica- tions (S. Zhou, S. Zhang, and G. Karypis, eds.), (Berlin, Heidelberg), pp. 318–329, Springer Berlin Heidelberg, 2012.

[20] B. Glasgow, A. Mandell, D. Binney, L. Ghemri, and D. Fisher, "Mita: An information-extraction ap- proach to the analysis of free-form text in life insur- ance applications," AI Magazine, vol. 19, pp. 59–72, 03 1998.

[21] J. Choi, J. Tetreault, and A. Stent, "It depends: De- pendency parser comparison using a web-based eval- uation tool," vol. 1, pp. 387–396, 07 2015.

[22] M. Honnibal and I. Montani, "spacy 2: Natu- ral language understanding with bloom embeddings, convolutional neural networks and incremental pars- ing.," 2017.

[23] A. Kormilitzin, N. Vaci, Q. Liu, and A. Nevado- Holgado, "Med7: a transferable clinical natural language processing model for electronic health records," 03 2020.

[24] B. Gaur, G. S. Saluja, H. B. Sivakumar, and S. Singh, "Semi-supervised deep learning based named entity recognition model to parse education section of resumes," Neural Computing and Appli- cations, pp. 1–14, 2020.

[25] UN, "Transforming our world : the 2030 agenda for sustainable development," UN General Assem- bly, 10 2015.

[26] Y. Bengio, P. Frasconi, and P. Simard, "Problem of learning long-term dependencies in recurrent net- works," pp. 1183 – 1188 vol.3, 02 1993.

[27] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, pp. 1735–80, 12 1997.

[28] City of Maddinson dataset https://data-cityofmadison.opendata.arcgis.com/datasets/police-incident-reports

[29] Spam Collection dataset obtained from https://www.dt.fee.unicamp.br/~tiago/smsspamcollection/