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AI CHATBOT for Agriculture IN RASAA Project ReportSubmitted in Partial Fulfillment of the Requirementfor the Award of the DegreeofBACHELOR OF TECHNOLOGY(Computer Science and Engineering)ToByKuluru Vineeth Kumar Reddy REG NO:18BCS043Karthick P SREG NO:18BCS038LaxmiNarayana K REGNO:18BCS037Under the Guidance ofDr. Uma SeshadriDEPARTMENT OF COMPUTER SCIENCEIIT, DharwadAPR-20211 CANDIDATE'S DECLARATIONWeherebycertifythattheworkwhichisbeingpresentedintheprojectreportentitled“AICHA TBOTforAgricultureINRASA”inpartialfulfillmentoftherequirementfortheawardoftheDegreeofBachelor ofTechnologyandsubmittedtotheDepartmentofComputerScienceofIndianInstituteofInformationTech nologyDharwad,isanauthenticrecordofourownworkcarriedoutduringaperiodfromFebruary2021toApri l2021underthesupervisionofDr. UmaSeshadri,DepartmentofComputerScienceandTechnology,IndianInstituteofInformationTechnolog y, Dharwad.Thematterpresentedinthisreporthasnotbeensubmittedbyusfortheawardofanyotherdegree of this or another Institute/University.Kuluru Vineeth Kumar ReddyKarthick P SLaxminarayana KThis is to certify that the above declaration made bythe candidate is accurate tothe exceptional of my knowledge.Date:Dr. Uma Seshadri-----
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ACKNOWLEDGEMENTSItisindeedagreatpleasuretoexpressoursincerethankstooursupervisorDr. UmaSeshadri,DepartmentofComputerScienceandEngineering,IITDharwadforhercontinuoussupporti nthisproject.Shewasalwaystheretolisten,adviseandshareherexpertisewithusat everystageofthe proje

development. She showed us different ways to approach a real world problem and the need to be persistent to accomplish any goal. She had confidence in us when we had doubted ourselves, and brought out the good ideas in us. She was always there to meet and talk about our ideas, share her expertise and views on developing a solid prototype, and to ask us good questions to help us think through our problems. Without her encouragement and constant guidance, we couldn't have finished this project on time. We are also indebted to our own team members for their rigorous efforts in questioning the most difficult cases and extracting the best out of it and also for their persistent coordination till the end.

Without their support and cooperation, this project could not have been finished. Kulu Vineeth Kumar Reddy Karthick P S Laxminarayana K3 CONTENTS Page No. Phase-1: Introduction 51.1 Abstract 51.2 AI and NLP 61.3 Natural Language Understanding (NLU) 9 Phase-2: RASA and RASA X 102.1 Introduction to RASA 102.2 Generating the NLU training statistics (intents and entities) 112.3 Domain, Custom movements and slots 162.4 RASA X 20 Phase-three: Problem identity and its significance 223.1 Problem identity and challenges 223.2 Requirements and specifications 233.3 Installing RASA and RASA X 253.3.1 Installing RASA 253.3.2 Installing RASA X 253.3.3 Deploying Rasa X 25 Phase-4: Proposed answer and implementation 334.1 Approach to remedy issues within the precise domains 334.2 The ML models and their scores 384.2.1 Data extraction and normalization 384.2.2 The Crop advice model 38 Phase-five: Conclusion and future scope 425.1 Conclusions 425.2 Future scope 435.3 How to apply our repository and make a contribution to our project 434 Phase-1 INTRODUCTION 1.1

ABSTRACT Chatbots are computer programs that simulate human conversation through voice commands or text chats or both. Chatbot, short for chatterbot, is an artificial intelligence (AI) feature that can be embedded and used via any foremost messaging applications. The goal of this project is to build a prototype of an AI chatbot to address the problems faced through farmers in numerous levels of the agricultural sector. Our AI chatbot has features ranging from providing the information on fertilizer consumption state wise, educating the farmers about the MSP rates in their respective states (for a limited crop varieties), acknowledging them to use specific fertilizer varieties to reduce their initial investment and suggest for proper crops to be grown based on the features like nutrient content of soil after having gone through soil testing (ex: N, P, K values of soil), live weather details of their residing location (ex: temperature, humidity, rainfall). The chatbot also provides these recommendations to the farmer in his native language (for demonstration we have used Kannada). Our chatbot is built exclusively using RASA, an open source Machine Learning framework which uses the RASA NLU for understanding the user intents and RASA Core to predict the best viable movement as a reaction from the chatbot based on a probabilistic version.

The chatbot uses the publicly available APIs from various government portals and publicly available dataset from open source communities like Kaggle to access the information required. The project also makes use of techniques such as input feature extraction from the raw data collected, which is fed as an input to the predictive Machine Learning model. It also uses the different datasets from these portals to make use of them for training an ML model for crop advice.

Phase-2 RASA and RASA X

2.1 Introduction to RASA

What are contextual assistants?

- Able to understand the context of the conversation, i.e. what the user has said previously and while/in which/how they stated it.
- Capable of knowledge and responding to different and sudden inputs.
- Can learn from previous conversations and improve in accuracy over time

Buildable today with Rasa.

Exploring Rasa

Rasa has 3 foremost additives that paintings together to create contextual assistants: Rasa

NLU: Rasa NLU is like the “ear” of your assistant—it helps your assistant understand what’s being said.

Rasa NLU takes user input in the form of unstructured human language and extracts structured statistics within the shape of intents and

entities.

- Intents are labels that represent the goal, or meaning, of a user’s specific input. For example, the message ‘Hello’ could have the label ‘greet’ because the meaning of this message is a

- Entities are important keywords that an assistant should take note of. For example, the message ‘My name is Juste’ has the name ‘Juste’ in it. An assistant should extract the name and consider it for the duration of the communication to keep the interplay

herbal.

1. Entity extraction is achieved by training a named entity recognition model to identify and extract the entities (in this example, names) from unstructured person messages

Core: Core is Rasa’s dialogue management component. It decides how an assistant should respond based on:

- 1) The content of the communication

- 2) The context.

Rasa Core learns by observing patterns in conversational data between users and an assistant.

X: Rasa X is a toolset for developers to build, improve and deploy contextual assistants with the Rasa framework. You can use Rasa X to:

- View and annotate conversations
- Get comments from testers
- Version and control

models

With Rasa X, you can share your assistant with real users and collect the conversations they have with the assistant, allowing you to improve your assistant without interrupting the assistant running in

2.2 Generating the NLU training statistics (intents and

entities)

The moodbot starter project contains a Data directory, where we will be able to find the training data documents for NLU and speak control functions. The Data listing includes documents:

- nlu.md-

the file containing NLU model training examples. This includes intents, which are user goals, and example utterances that represent those intents. The NLU training data also labels the entities, or important keywords, that the assistant should extract from the example

utterance. 1. Intents are defined using a double hashtag. Each intent is followed by multiple examples of ways a person may specify that intent. eleven

2. Entities are labeled with square brackets and tagged with their type in parentheses. (screenshot of entities through laxy) 12 ● stories.md - the report containing tale statistics. Stories are instance give up-to-give up conversations 13

Rules are a type of training data used to train your assistant's dialogue management model. Rules describe quick portions of conversations that should usually observe the identical path. PRE-CONFIGURED

RASA PIPELINES: Key Concepts ● NLU model -

An NLU model is used to extract meaning from text input. Training an NLU model on this data allows the model to make predictions about the intents and entities in new user messages, even when the message doesn't match any of the examples the version has visible before. ● Training pipeline -

NLU models are created by a training pipeline, also referred to as a processing pipeline. A training pipeline is a sequence of processing steps which allow the version to examine the schooling statistics's underlying patterns. ● Word embeddings -

Word embeddings convert words to vectors, or dense numeric representations based on multiple dimensions. Similar words are represented by similar vectors, which allow the technique to capture their meaning. Word embeddings are used by the training pipeline components to make text data understandable to the machine learning version. 14 Rasa comes with default, pre-configured

pipelines 1. Pretrained_embeddings_spacy: Uses the spaCy library to load pre-trained language models, which can be used to symbolize every phrase in the user's enter as phrase

embeddings. 2. Supervised_embeddings: Unlike pre-

trained embeddings, the supervised_embeddings pipeline trains the model from scratch using the data provided in the NLU training data file. 15 2.3 Domain, Custom movements and slots Domain File in

Rasa: The domain is an essential component of a Rasa dialogue management model. It defines the environment wherein the assistant operates, such as: ● What the person means: specifically, what intents and entities the version can understand. ● What responses the version can offer: including utterances or custom movements. ● ● What to mention next: what the version must be prepared to respond

with. ● What info to remember: what information an assistant should remember and use throughout the communicate. sixteen 17

Actions: This section called `actions` should contain the list of all utterances and custom actions an assistant should use to respond to user's inputs. These should come from your stories data in the `stories.md` report. Custom Actions in

Rasa: Adding response templates directly to the domain file is the easiest way to define the message an assistant sends the user once a specific utterance is predicted. But there is another way to achieve the same result - by creating custom actions. Custom actions are response actions which include custom code. That custom code can define anything from a simple text response to a backend integration -

an API call, connecting to the database, or anything else your assistant wishes to

do. Custom actions are defined in a file called `actions.py`, containing python code, as the file extension

suggests. ● **tracker** keeps track of what happens at each point within a dialogue - what intents were predicted, which entities were extracted, as well as different records. ● **dispatcher** is the detail that sends the response back to the person (screenshots of custom movements)

Rasa: Another important element of the domain file - very important for dialogue management in Rasa - is slots.

Slots function as the assistant's memory, and are used by your assistant to remember important details throughout the conversation and apply those details in context to drive the conversation. Slots act as a key-value pair to store information critical to the conversation with the user. This information can be provided by the user (e.g., entity values extracted by the NLU model) or gathered from outside the conversation (e.g., results extracted from the outside database).

2.4: RASA X What is Rasa

X? Rasa X is a UI tool for developers, used to improve assistants built with Rasa Open Source. It's intended to remedy issues: ● First, to make it less complicated to leverage actual conversations as training statistics. ● Second, to offer a manner to check beyond conversations for styles or errors

Phase-3 Problem identity and its significance 3.1 Problem identity and

challenges The share of agriculture in GDP being close to around 20 percent in 2020-21, and also with the generations changing, the shortage of people practising agriculture exponentially declining, economically speaking "less supply more demand" urged our strong gut to believe this is the future trending field maybe 5 from now or 10 years to be optimistic, this all vital point triggered the team to work on the important phases of agriculture to improve the farmers produce, as a result assisting each the farmers as nicely as the kingdom to prosper.

After rigorous research and analysis, the main challenges that were identified to be of utmost importance for the farmers was to find solutions in the domains of selling their agricultural produce for reasonable prices, efficient fertilizer usage for crops and proper crop to be grown in their fields to get most produce.

But the task to be done is not as simple as it looks ("Easier said than done"), here are the major demanding

situations to be appeared

upon: ●Lack of proper and structured training data: Now the problem here lies in the fact that most of the data collected from the government portals are raw data.

Hence, now to train our model for the crop recommendation, we need to filter the important feature vectors to be used and apply the techniques such as mean normalization to make the ML model obtain a globally optimized answer.

●Limited API access to government data: The second challenge that was faced by the team was that only a limited datasets from the government portals were allowed access for public API calls. Also getting access to real world data, which is like an important asset these days is expensive since the world is on the verge of cutting-edge technologies. So, it is really hard to gather the data that we are badly in need of due to constraints like cost, privacy, credibility and other valuable concerns.²²

●The very new RASA framework: Although RASA is a powerful Machine Learning framework to build complex models, it was very recent and new (founded in 2016), hence none of our team members knew about how to code and also about its features.

Hence the team had to completely understand the technology from scratch. The team also struggled a lot to find solutions for errors due to very less resources available online as well as due to less community members available for the framework to discuss the issues. ●Problem of deployment: Any project becomes completed only when it reaches the public to experiment with it and also help the development team to improve the features of the chatbot. An important issue faced by the team at this stage was that most of the online resources and RASA community deployed the model on GCP, but we were unable to access it because of its hard policies on credit card (being students, really hard to possess credit cards since no source of income), this problem compelled the team to migrate to AWS, where there are references or resources to deploy RASA-

SERVER was not even available on the official RASA documentation as well as on other side, scarcity of being charged closely restrained our scope of experimentation.^{three}

2 Requirements and specifications

Hardware & OS Requirements: Here are the minimal and endorsed hardware specs and OS requirements: Install script Manual installation Operating

System Ubuntu 16.04/18.04/19. 10 Debian 9/10 CentOS 7 / eight RHEL

8 a modern Linux or Windows distribution that can run Docker vCPUs Minimum: 2 vCPUs Recommended: 2-6 vCPUs 23 RAM Minimum: 4GB RAM Recommended: 8GB RAM Disk

Space Recommended: 100GB disk space available Port requirements: Port Service 22 SSH SSH

access. 80 HTTP Web utility access. 443 HTTPS Web utility over HTTPS access Supported Browsers: The net interface goals to guide browsers that meet the following criteria: ●0.2% marketplace

proportion ●now no longer Internet Explorer ●now no longer Opera Mini Software

Requirements: Operating System: Windows and linux Technology: PYTHON, RASA Dependencies: pickle, pandas, numpy, scikit-examine, matplotlib, seaborn

2.3 Installing RASA and RASAX

2.3.1 Installing RASA

Quick Installation

```
pip3 install -U pip
pip3 install rasa
```

You can create a brand new undertaking through running: `rasa init`

Step-through-step Installation Guide

You can observe respectable rasa documentation part ([link to be included](#))

2.3.2 Installing RASA X

Rasa X: ● layers on pinnacle of Rasa Open Source and facilitates you build a higher assistant ● is a free, closed supply device to be had to all developers ● may be deployed anywhere, so your schooling statistics stays secure and proprietary

2.3.3 Deploying Rasa X

Configure the VM instance

25 Step 1 : Log in for your AWS Console and navigate to Services-> Compute-> EC2. Click Launch Instance.

Step 2 : Choose an Amazon Machine Image(AMI)-> Go to Ubuntu Server 20.04 LTS> choose.

26 Step three : Choose an example kind ast2.medium-> Configure Instance Details

27 Step 4 : Keep all default settings as it's far and click on on Next: Add Storage

Step five : Here change size (GiB) to one hundred after which click on Next: Add Tags

28 Step 6 : No modifications right here simply click on on Next: Configure Security Group

Step 7 : Here Add two Rules HTTP and HTTPS and then click on Review and Launch

29 Step eight : Just click on on Launch and your example may be created.

30 Step nine : Connect for your created instance

Step 10 : Install the desired dependencies

31 Step eleven : Check for the documents gift within the rasa folder.

Step 12 : Open the ipv4 cope with of the created instance and connect with the github repository.

Step 13 : Eureka! Now all the features of RASAX can be found and model can be improved by sharing to multiple customers.

4.1 Phase-4 Proposed answer and implementation

4.1.1 Approach to remedy issues within the precise domains

Project Flow chart:

33 As mentioned in the problem description, the main areas of focus is on the fertilizer recommendation, crop recommendation, etc.

The important queries required by the farmers were taken into account and around 5 story paths were designed accordingly. Let's have a look at every of the tale paths.

1. About us path:

2. Crop fee path (carried out the usage of api calls): ● This is one of the paths that uses an api call. We have taken 3 major crops (rice, cotton and jute) and use an api name to the statistics.gov.in website. ● instance ([https://api.statistics.gov.in/resource/6e8e9a24-491d-4bcb-bdf4-bb0724cbb926?api-key=579b464db66ec23bdd000001cdd3946e44ce4aad7209ff7b23ac571b&format=json&offset=0&limit=one hundred&filters\[state_ut\]=Andhra Pradesh](https://api.statistics.gov.in/resource/6e8e9a24-491d-4bcb-bdf4-bb0724cbb926?api-key=579b464db66ec23bdd000001cdd3946e44ce4aad7209ff7b23ac571b&format=json&offset=0&limit=one hundred&filters[state_ut]=Andhra Pradesh)) where api-

key is the unique key obtained by signing into the data.gov. in website to gain access to study records from the government

database. ● But instead of Andhra Pradesh we provide the state that was extracted from the farmer during conversations in rasa. This gives us the output in the form of a json

format. ● Now we can extract only the required information that is needed by using indexing just like arrays. (ex: current['records'][0]['_2017_18__prod__as_per_cab_meeting_dt__18_6_19__qty__in_lakh_bales_'] extracts from the govt database only the produce as in step with cab assembly in lakh bales within the respective state).

● Once this step is over we can display only the important information extracted about the crop and the state in which it was grown as responses uttered by the chatbot. 34 three. Fertilizer

path: ● We follow the same steps as mentioned in price path to extract information about fertilizers as nicely the usage of api calls. ● [https://api.statistics.gov.in/resource/1a800a9a-7c6e-42ba-b238-6ae1c17d5195?api-](https://api.statistics.gov.in/resource/1a800a9a-7c6e-42ba-b238-6ae1c17d5195?api-key=&format=json&offset=0&limit=10&filters[state_u_t_]=.format(api_key,loc))

key=&format=json&offset=0&limit=10&filters[state_u_t_]=.format(api_key,loc) this is 35 4. Fertilizer advice path: ● This is a path which uses the recommendation that was provided by a crop health knowledge

website. ● We have stored the details collected in the form of a dictionary and call the specific information in the dictionary based on the level of nutrients the soil (N, P, K values) has when compared to the national standard mentioned in the website and offer the required guidelines based on that. 36 five. Crop advice

path: In the crop recommendation application, the user can provide the soil data from their aspect and the utility will expect which crop must the person

grow. ● This is the most essential part of the AI chatbot which gives suggestions about what crop to grow using predictions by an ML model. We shall see a detailed analysis of the various ML models that were used and their respective scores in the coming section. 37 4.2 The ML fashions and their scores 4.2.1 Data extraction and

normalization: This step is needed because the data extracted from govt portals being completely raw, we need to extract only the required features to train our model. Now from the fertilizers.

csv(N,P,K,phasfeatures) and cropdata.csv(temperature, humidity, ph and rainfall) are to be merged so that more functions may be used to educate our statistics version. The labels of the very last version are as follows: array([rice, wheat, mungbean, tea, millet, maize, lentil, jute, coffee, cotton, groundnut, peas, rubber, sugarcane, tobacco, kidneybeans, mothbeans, coconut, blackgram, adzuki beans, pigeonpeas, chickpea, banana, grapes, apple, mango, muskmelon, orange, papaya, pomegranate, watermelon], dtype=object) 4.2. 2 The Crop advice version: The following are the functions which

are utilized by our ML version for crop advice: Index([N, P, K, temperature, humidity, ph, rainfall, label]) Comparing accuracy from distinctive ML fashions that were built: 1. Gaussian naive bayes: 38 2. Decision tree: three. Support Vector Machine: 39 4. Logistic Regression 5. Random Forest: forty 6. XGBoost: Final accuracy evaluation of all of the fashions: forty one

As from the above figure, we can say that random provides a significant accuracy level for our ML model to make proper predictions, hence we save this model into a pickle file and import that into rasa to assist our bot show the predicted crop. Phase-5 CONCLUSION AND FUTURE

SCOPE 5.1 Conclusions: We have used the Al chatbot to its newest level into the field where it was least exposed (Agricultural sector, Farming). We hope to have created a foundation for many similar future development to help the Agricultural sector progress and prosper with such new and fascinating technologies. This project has also shown that Al chatbots can not only be used for business management, but can also revolutionize and change the way that the current Agricultural device

works. This project was a genuine attempt by the team members to make Al chatbots revolutionize the present agricultural device with utmost diligence. five. 2 Future

scope: 1. The language used to implement the project was in English, this can however be extended to multiple languages with an option for the farmer to choose from with the chatbot suggestions additionally within the language chosen by the farmer. 2.

With more amount of training data in hand, the model could be trained rigorously and also with extra enter functions including the season in which the crop is grown,

etc. three. A voice can also be added to the utterances by the bot in the native language which the farmer chooses (including Alexa, Siri, etc.) forty two

4. Another feature of enabling the farmer to sell their produce in the nearest available shop that provides the best rates and also connects the farmer to the best fertilizer selling shops in their locality.

(This feature could involve integrating our chatbot with Google Maps). five. 3 How to apply our repository and make a contribution to

our project Step 1: Clone our GitHub repository into your desired location using the below link: <https://github.com/kuluruvineeth/Agrosahakar> Step 2: create a VM example on any cloud platforms such as AWS, Azure, GCP,

Heroku. Step 3: Deploy RASAX server on VM instance created in step 1 as mentioned in the phase 2. For detailed information please refer to the official RASA documentation: RASA documentation Step 4: Now your

RASAX server may be up and running. Step five: Connect your repository to the RASAX server: 1. Generate SSH

keys: ● Navigate back to your terminal. If you've closed the connection to your VM instance, log again

in.●Run the subsequent command to generate a public and private SSH key: `ssh-keygen -t rsa -b 4096 -f git-deploy-key`

key●After the key has finished generating, you can run the `ls` command in the `/rasa/etc` directory to see the newly created keys: `git-deploy-key` (the private key) and `git-deploy-key.pub` (the general public key).2.

Save the general public key in

GitHub:●We'll print the public key to the terminal so we can copy and save it in our GitHub settings. Run the subsequent command to view the public key: `cat git-deploy-key.pub`●Copy the complete contents. forty three

In your GitHub repository, navigate to `Settings > Deploy keys`. Click the `Add deploy key` button and paste your public key into the `Key box`. Give the key a title to identify it, like `medicare-rasax`, and be sure to check the box to allow `Write` permissions. Click `Add`

key.three. We'll establish the connection between the Rasa X instance and GitHub repository by making a POST request to this Rasa X API endpoint.4. The JSON request frame includes 3 portions of records:●`repository_url`-

The SSH URL for your GitHub repository, e.g. `kuluruvineeth/Agrosahakar.git`●To get the URL for your repo, click the `Clone or download` button on your GitHub repository and choose the `Use SSH`

link.●`target_branch`-The GitHub repository branch where Rasa X should push and pull modifications, e.g. `master`●`ssh_key`- The non-public SSH key generated for your

server. To copy the private key, run the following command in the `/etc/rasa` folder on your server: `cat git-deploy-key` Copy the complete contents of the key, such as the lines `-----BEGIN RSA PRIVATE KEY-----` And `-----END RSA PRIVATE KEY-----` Once you've assembled the JSON object, you'll have something like this: We'll save this JSON object in a file called `repository.json`, in the `/rasa/etc` folder on the server5. First, let's create that file: `touch repository.json`●Open the report to edit

it: `nanorepository.json` Paste the JSON object into the file. Press `Control + X` to exit the editor, and confirm `Y` to save your modifications while

prompted.●Head back to the terminal. Still in the `/etc/rasa` directory, run the following `cURL` command which you will get clicking on `upload model` button in RASAX interface, replacing the Rasa X server URL and API key values together along with your own: `curl --request POST --url http://api/projects/default/git_repositories? api_token= --header content-kind: utility/json --statistics-binary`

@`repository.json`●Check the connection by navigating back to the Rasa X dashboard in your browser and checking the `Integrated Version Control` icon in the bottom left corner. If the connection was successful, you'll see either a green indicator, meaning Rasa X is up to date with the GitHub repository, or a yellow indicator, mea

ning RasaX has changes that need to be pushed to GitHub. Step 6: Set up the Actions Server: 45

- We have one more thing to configure: the assistant's custom actions server. To do this, we'll place the assistant's custom action code within an actions directory on the server.
- Connect to your server and make sure you're in the `/etc/rasa` directory. In your terminal, run the following command to create the actions directory and two files interior it: `__init__.py` and `actions.py`.
- Run `nano actions/movements.py` to edit the newly-created `actions.py` report.
- Paste the code from your assistant's `actions.py` file into the blank file, save, and close the editor.
- Then, we need to create a `docker-compose.override.yml` file. This file instructs docker-compose to spin up a custom actions server when the RasaX server starts up.
- Let's create that report: `contact docker-compose.override.yml`

Open the report editor: `nano docker-compose.override.yml`

And upload the subsequent contents:

```
version: '3.4'
services:
  app:
    image: rasa/rasa-sdk:latest
    volumes:
      - ./movements:/app/actions
    expose:
      - 5055
    depends_on:
      - rasa-production
```

- Here, we're reusing the `rasa-sdk` image to run our custom actions, and we're specifying that the actions server will listen on port 5055. The actions server depends on the `rasa-production` service, which is 46

responsible for running the trained model, parsing intent messages, and predicting movements.

- Once you've saved the file, you can restart the RasaX docker container and the assistant may be absolutely purposeful on RasaX. `sudo docker-compose up -d`

Step 7: Eureka!!! You have done the complete setup and are ready to use our chatbot. Feel free to proportion your feedback in github.

More Screenshots 47 forty eight CROP PRICE VIDEO FERTI INFO VIDEO FERTI RECOMMENDATION VIDEO CROP RECOMMENDATION VIDEO 49 50

MATCHED SOURCES:

[twitter.com](#) - <1>Compare

<https://twitter.com/hashtag/Antibioticresistance>

[www.tandfonline.com](#) - <1>Compare

<http://www.tandfonline.com/action/cookieAbsent>

www.irs.gov - <1>*Compare*

<https://www.irs.gov/publications/p583>
