

A Major Project Proposal Report on

## **Detection, Tracing and Tracking of Health Misinformation**

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Submitted by:

**Aman Sheikh, 211506**  
**Prashanta Rokaya, 211528**  
**Shikshya K.C., 211541**  
**Shreya Khanal, 211546**

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**Department of IT Engineering**  
**NEPAL COLLEGE OF**  
**INFORMATION TECHNOLOGY**  
Balkumari, Lalitpur,Nepal



# ABSTRACT

Plant Disease Detection System is a mobile application that helps users detect plant diseases by analyzing uploaded images of plant leaves. The system uses machine learning, specifically convolutional neural networks (CNNs), to identify diseases based on visual patterns and symptoms. Once a disease is detected, the system provides recommendations for treatment and prevention. The goal of this project is to simplify plant care by enabling users to easily diagnose diseases, which typically require expert knowledge. The system allows users to upload images of plant leaves and receive instant feedback about possible diseases, along with actionable recommendations for care. The system is built using Flutter with a machine learning model powered by TensorFlow. The model is trained on datasets like PlantVillage, which includes images of common plant diseases. This makes PlantCare an accessible and effective tool for both hobbyists and professional gardeners, helping them manage plant health more efficiently.

## Keywords

*PlantCare, MachineLearning, CNNs, Flutter, TensorFlow*

# **Contents**

<b>1</b>	<b>INTRODUCTION</b>	<b>1</b>
1.1	PROBLEM STATEMENT . . . . .	1
1.2	PROJECT OBJECTIVES . . . . .	2
1.3	SIGNIFICANCE OF THE STUDY . . . . .	2
1.4	SCOPE AND LIMITATION . . . . .	3
<b>2</b>	<b>LITERATURE REVIEW</b>	<b>4</b>
<b>3</b>	<b>PROPOSED METHODOLOGY</b>	<b>6</b>
3.1	SOFTWARE DEVELOPMENT LIFE CYCLE . . . . .	6
3.2	TECHNOLOGIES USED . . . . .	8
<b>4</b>	<b>SYSTEM DESIGN</b>	<b>9</b>
4.1	USE CASE DIAGRAM . . . . .	9
<b>5</b>	<b>PROPOSED DELIEVERABLES</b>	<b>10</b>
<b>6</b>	<b>PROJECT TASK AND TIME SCHEDULE</b>	<b>11</b>
6.1	GANTT CHART . . . . .	12

## List of Figures

1	Incremental model	7
2	Usecase Diagram	9
3	Increment 1	12
4	Increment 2	12
5	Increment 3	13
6	Increment 4	13
7	Increment 5	14
8	Increment 6	14

# 1 INTRODUCTION

The rapid expansion of social media platforms has transformed the way people access and share health related information. While these platforms provide immediate access to medical knowledge, they are also responsible for the widespread of health misinformation which poses significant risks to public health [9]. Particularly in countries like our Nepal older generation such as members of Generation X are more prone to believing unverified health claims through forwarded messages and social media posts which can lead to harmful decisions regarding their health.

Health misinformation on social media can be seen in multiple forms that can range from exaggerated claims about treatment to false narratives regarding different diseases [11]. These studies highlight the urgent need for automated systems that are capable of detecting misleading content.

Recent advancements in AI have provided tools to tackle misinformation. These systems analyze both text and images to spot false content, helping to identify misleading posts quickly [13]. These methods use advanced AI techniques to understand and analyze content that allows the system to identify misinformation.

Tracking the source of misinformation is also equally important. Methods like crowdsourcing and machine learning can follow where false information started and how it moves through social media [8]. But current solutions often struggle with new forms of misinformation or fail to combine detection with tracing and tracking [11]. Studies emphasize the need for approaches that not only identify false content but also understand its impact [4].

By automatically identifying false health information, finding its source and tracking its spread, this system will help provide reliable guidance to users, particularly those who are more likely to be influenced by misinformation [6, 12]. Hence, this project aims to develop a system that can detect, trace and track health misinformation online.

## 1.1 PROBLEM STATEMENT

Social media makes it really easy for people to find health information but it also makes it easy for wrong or misleading health information to spread. Many people, especially older adults believe what they read online without checking if it's true. This can lead to wrong health decisions like trying unproven treatments or ignoring proper medical advice.

Currently most tools that try to fight misinformation are limited. They might detect some false claims but they don't always check if the claim is true, where it came from or how it spreads. This leaves people confused and also makes it hard for health authorities to stop false information from spreading.

Our project aims to solve this problem by building a system that can read health posts in image and textual format, check them against reliable medical sources and also tell if it is true or false.

## **1.2 PROJECT OBJECTIVES**

The main goal of this project is to build a system that helps people to identify which health information is true or false. The system will make it easier for users to understand if the claim is reliable, where it originated from and how it spreads.

The objectives of this project are:

- Extract factual health claims from posts, articles, images
- Retrieve relevant evidence from trusted medical sources like WHO, CDC, CoAID
- Detect health-related misinformation in social media posts, news, articles
- Trace the source of health misinformation
- Track spread of misinformation across social media platforms

## **1.3 SIGNIFICANCE OF THE STUDY**

Health misinformation spreads quickly across online platforms reaching people who trust what they read without verifying it. Understanding the importance of detecting, tracing and tracking such misinformation is crucial for all individuals(users) and health authorities as well. The following points highlight the significance of the study:

- Helps to identify false health information: The system enables users to detect misleading or incorrect health claims on online platforms that helps them avoid being misinformed.
- Monitoring health misinformation: By tracing the source and tracking the spread of misinformation, the system helps users see where false claims are coming from and how they circulate online.

- Promotes informed decision making: With verified evidence, users can make safer choices about health advice or medicines.
- Reduces personal risk from misinformation: By limiting exposure to false claims, the system protects users from potentially harmful advice.

## **1.4 SCOPE AND LIMITATION**

### **SCOPE:**

- Detects health-related misinformation in online platforms like social media posts, news, articles
- Traces the source of misinformation showing where false claims originated from
- Tracks how misinformation spreads across online platforms
- Provides users with verified evidence to support health claims

### **LIMITATIONS:**

- Accuracy limited on availability and quality of reliable evidence online
- Cannot verify claims in languages not supported by the system's translation module
- Real time tracking of misinformation is limited by platform restrictions
- Does not provide medical advice, only informs users about the reliability of information

## 2 LITERATURE REVIEW

Health misinformation on social networks has become a major problem around the world. This has led to much research on its patterns, effects, and ways of fighting it with technology. A fundamental study by Papanikou et al. (2024) suggests that misinformation expands rapidly due to user engagement dynamics, echo chambers, and algorithmic amplification of deceptive content [9]. The authors give a detailed look at IT-based methods such as machine learning, crowd verification, and network analysis that have been used to find and keep an eye on false health information [9]. Expanding on this, a systematic review by Suarez-Lledo and Alvarez-Galvez (2021) confirms that misinformation is prevalent across all major platforms, especially within topics like vaccines, diets, pandemics, and chronic illnesses [11]. They emphasize that misinformation continues to spread farther and faster than verified information, because of emotional narratives and sensational structuring [11].

Al-alshaqi et al. (2025) show additional developments in detection models with a BERT-based multimodal model that combines text and image data [2]. Their findings highlight how crucial context-aware representations are for spotting false health news [2]. Upadhyay et al. (2023) demonstrate improvements in linguistic-based detection by integrating socio-contextual cues into BERT, which enhances the detection of fake health news through social metadata and user behavior patterns [12]. In addition, Al-Ahmad et al. (2021) emphasize adaptability during quickly evolving health crises by proposing an evolutionary algorithm for COVID-19 misinformation detection [1].

Multi modal analytical techniques are becoming more popular as misinformation detection becomes more complex. Wang et al. (2020) show that image–text fusion considerably improves the accuracy in detecting medical misinformation by suggesting a deep learning model that incorporates both textual and visual cues [13]. Their results highlight the importance of multi-modal systems because misleading posts often have deceptive images [13].

A social perspective is brought by Pulido et al. (2020), who explore how positive social impact and scientific voices on social media can counter fake news [10]. They found that authoritative health content, when paired with community engagement, contributes significantly to reducing misinformation spread [10]. From a global public health standpoint, Do Nascimento et al. (2022) conduct a systematic review of reviews and conclude that infodemics pose threats similar to biological epidemics [6]. They emphasize the need for coordinated, multi-sectoral strategies that combine regulation, technology, and public education [6].

Cianciulli et al. (2025) offer a scoping review of the public health landscape that demonstrates the growing adoption of digital tools and artificial intelligence by governments and health organizations [5]. They document interventions like risk communication dashboards, robotic fact-checking, and myth-busting campaigns powered by bots [5].

Lastly, Fridman et al. (2025) examine false information about untested cancer treatments on social media and demonstrate that straightforward linguistic indicators, such as readability and certainty markers, can accurately detect false information [7].

### **3 PROPOSED METHODOLOGY**

#### **3.1 SOFTWARE DEVELOPMENT LIFE CYCLE**

This project follows the **Software Development Life Cycle(SDLC)** using the **Incremental Model** allowing the system to be developed in fully functional modules. Each increment adds new capabilities to the system. The whole development process is divided into six increments listed below:

##### **1. Increment 1: Requirement Analysis & Base AI Prototype**

- Conduct requirement analysis and define scope of the system
- Collect datasets for AI model
- Develop preliminary AI model to detect health misinformation
- Prepare technical documentation

##### **2. Increment 2: Evidence Index, AI Model(Tracking), OCR Research & Mobile Application UI/UX**

- Design and integrate the evidence indexing system
- Begin mobile application development (UI/UX creation and OCR Research)
- Develop AI model to track health misinformation
- Research OCR module
- Documentation

##### **3. Increment 3: Mobile App Development, AI Model(Tracing), OCR Design & Backend Design**

- Development of core mobile application
- Begin OCR design
- Develop an AI model to trace health misinformation
- Begin designing backend system
- Documentation (ongoing)

#### 4. Increment 4: Backend Development, AI Model Completion & API Integration

- Complete backend development
- Integration of API for AI, OCR, and mobile application
- Finalize AI model and refine it
- Documentation (ongoing)

#### 5. Increment 5: System integration (AI + App + Backend)& Feedback System

- Integrate AI, mobile app and backend
- Implement feedback collection system
- Documentation (ongoing)

#### 6. Increment 6: Testing and Bug Fixing

- Conduct complete system Testing
- Identify and fix bugs
- Prepare deployment-ready build
- Complete Documentation

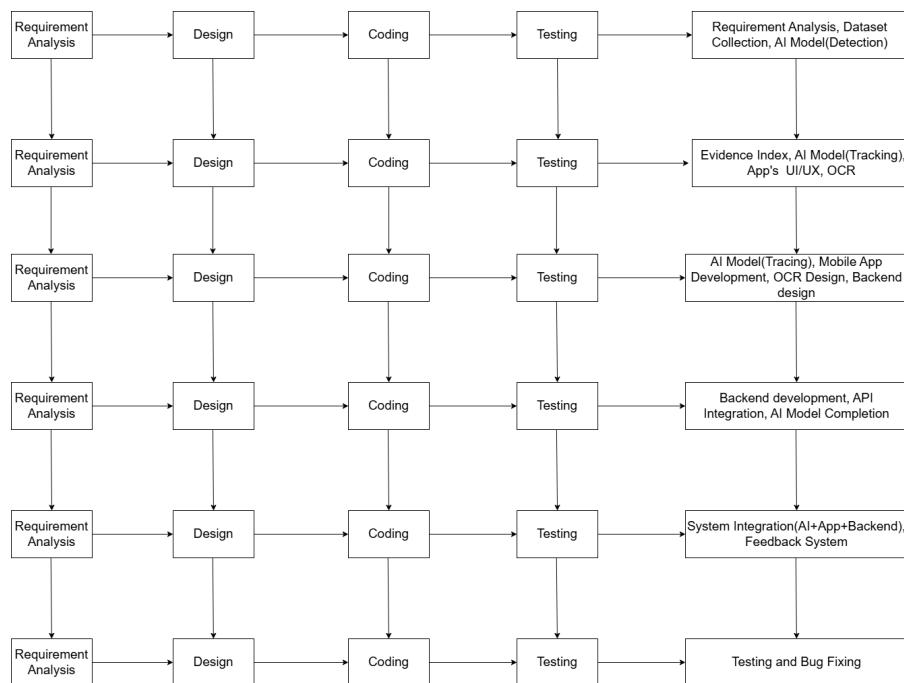


Figure 1: Incremental model

### 3.2 TECHNOLOGIES USED

Technologies to be Used	Subject
HTML	Structure of webpages
CSS	Styling the components of webpages
JavaScript	Interactivity of webpages
PHP	Backend
Laravel	Framework of PHP
Flask	API Integration
Google Colab	Develop machine learning model
MySQL	Backend Database
Python	Deploy machine learning model
Git and Github	Version Control
VS Code	Code Editor
LaTeX	Documentation

Table 1: Technologies used

## 4 SYSTEM DESIGN

### 4.1 USE CASE DIAGRAM

A use case diagram is a visual representation of the interactions between actors (in our case: User, and Admin) and the plant disease detection system. It shows the different use cases or functionalities provided by the platform and the relationships between the actors and these use cases.

PlantCare useCase Diagram.png

Figure 2: Usecase Diagram

## **5 PROPOSED DELIVERABLES**

- AI Model: A trained ML model developed from datasets to classify health related misinformation capable of detecting and classifying health related misinformation spreading across online platforms
- Misinformation detection module: A system that integrates the AI model, processes user's input and displays results to the user
- Mobile Application: A functional application that allows users to submit content and view analysis report
- Tracing and Tracking system: A module that maps from where the misinformation originates and how it spreads across the platforms
- Technical Documentation: Documentation covering the system's architecture and model details

## **6 PROJECT TASK AND TIME SCHEDULE**

The project schedule has been designed as per the requirements involved. The project is estimated to be completed in about 12-13 weeks. Research and requirement analysis is to be done first and is also crucial for overall working of the project explaining the lengthy time requirements. The project will be well documented on both the iterations reporting the working of the project at each time. Debugging and testing are to be done prior to the completion of the project.

TASK	APPROX DURATION IN DAYS
Requirement Analysis and Specification	41
System Design	11
Coding and Implementation	20
Testing and Debugging each Module	19
Documentation	60

Table 2: Time Schedule

## 6.1 GANTT CHART

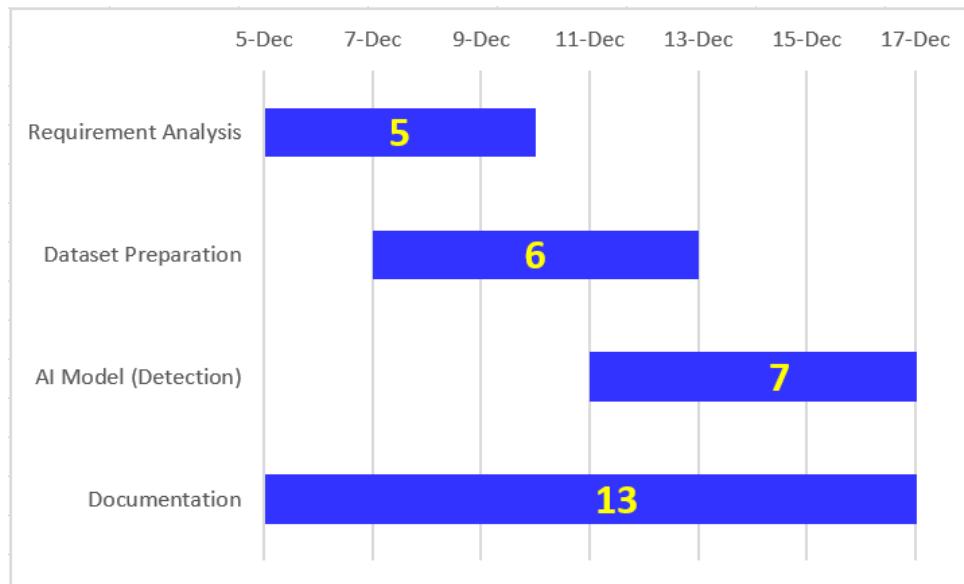


Figure 3: Increment 1

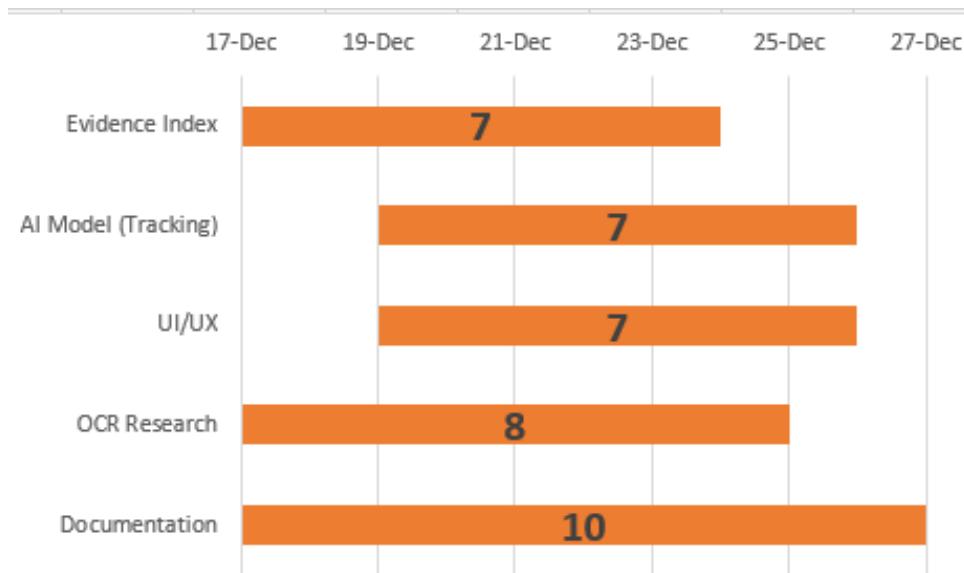


Figure 4: Increment 2

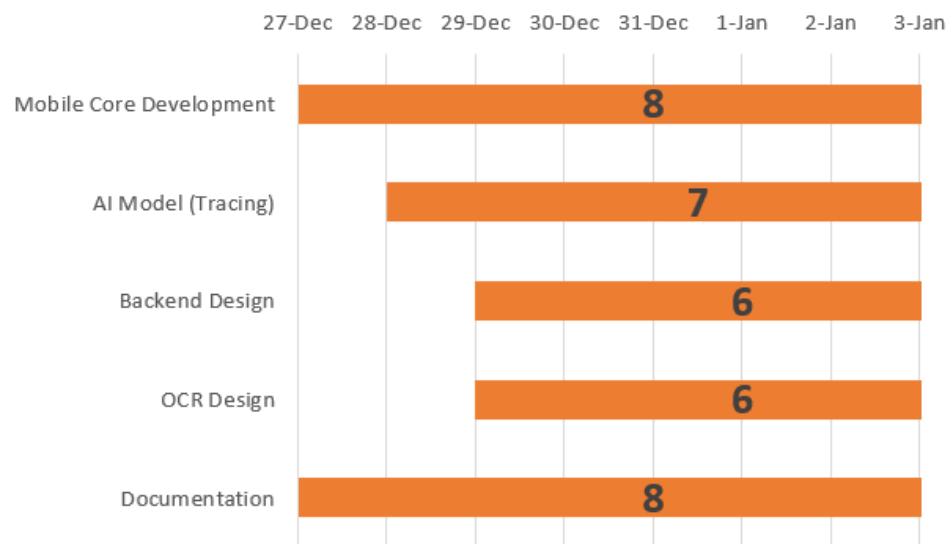


Figure 5: Increment 3

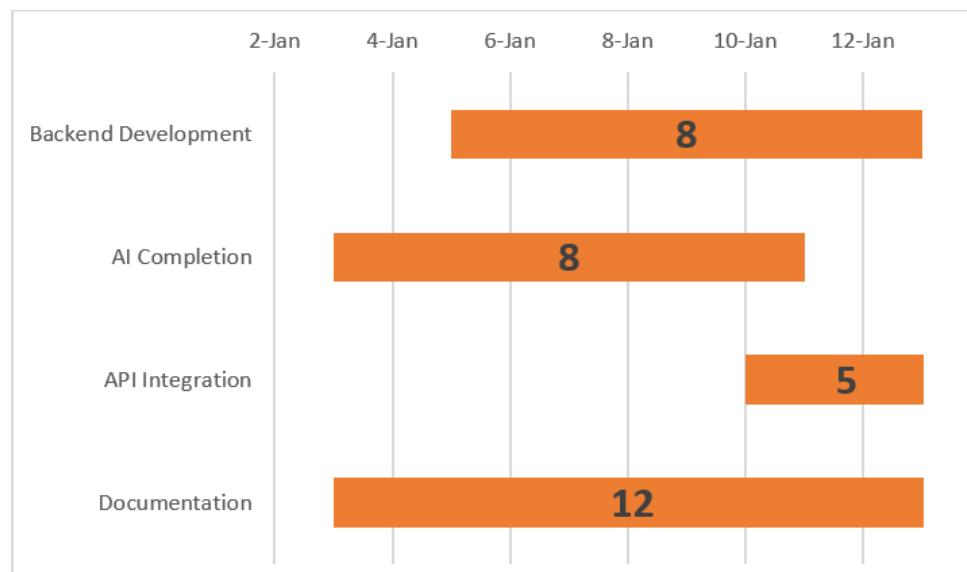


Figure 6: Increment 4

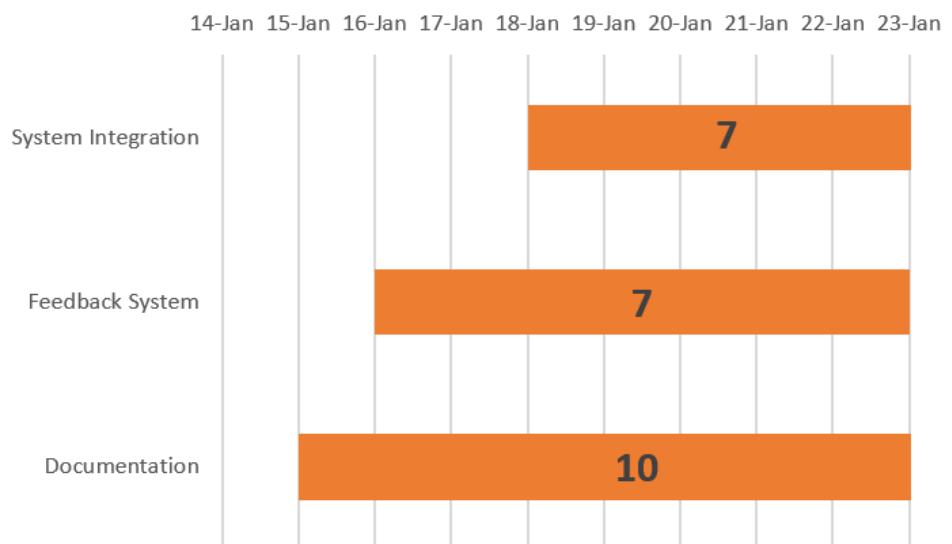


Figure 7: Increment 5

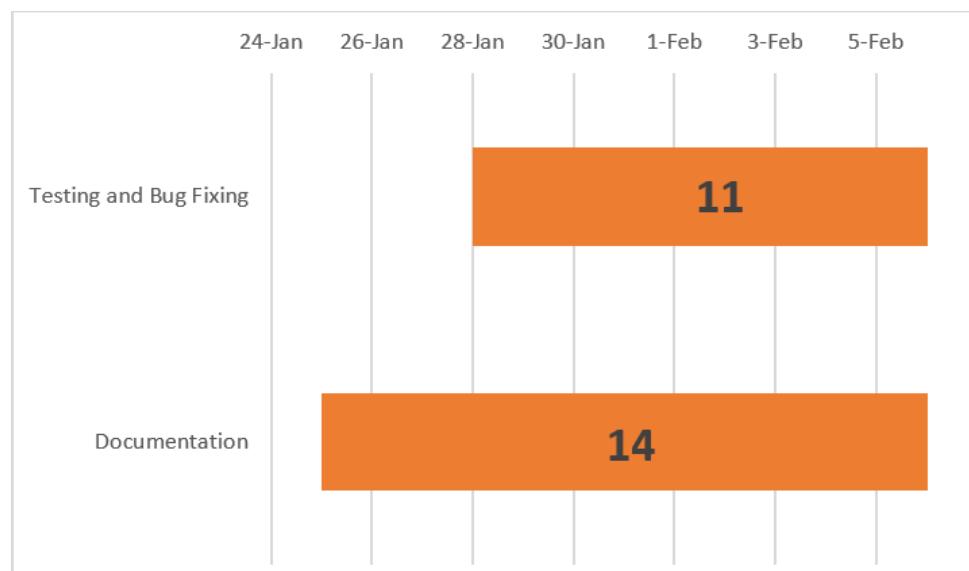


Figure 8: Increment 6

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