Project Title: Offline AI-Powered Community Support and Vulnerability Prediction System for Conflict-Affected Areas in Myanmar

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1. Literature Review

1.1 Introduction

This project focuses on empowering and providing support to communities in war-affected, rural and politically oppressed areas of Myanmar. These communities face significant risks, including poverty, food insecurity, health crisis, and natural disasters, severely disrupting schooling, affecting children's access to quality education. These challenges emerged from limited internet connectivity, isolating residents from critical aid and learning materials or resources. This research directly addresses the needs and satisfies alignments with multiple Sustainable Development Goals (**SDGs**), such as,

i. SDG 1 – No Poverty
ii. SDG 3 – Good Health and Well-being
iii. SDG 4 – Quality Education

A review of existing literature is necessary to establish the foundation for the project's hybrid design, investigating two distinct related fields of research; firstly, this study will explore established methods for vulnerability prediction, using Machine Learning (ML) and satellite imagery for at-risk populations identification. And as secondary part, in order to function in "Low-connectivity environments", the current technology for AI-powered communication systems is examined, including both powerful LLM-based offline platforms and lightweight NLP-based chatbots. This literature review will demonstrate how this project will be built based on some proven research trends by bridging the gap between identifying vulnerable communities and delivering them offline, by giving actional support.

1.2 Organizations

This literature review is organized thematically into two main sections which directly address the project's hybrid design.

Theme 1: Vulnerability Prediction using Machine Learning and AI – This section will review literature based on the use of machine learning, deep learning and satellite imagery for the prediction of poverty, educational disruption, economic hardship, welfare, and other vulnerabilities in alignment with the corresponding Sustainable Development Goals (SDGs).

Theme 2: Offline AI Chatbot Systems for Aid and Education – In this section, the development of AI-powered chatbots will be reviewed which can operate in low-connectivity or offline environments, comparing high-performance Large Language Model (LLM) based systems with lightweight NLP and rule-based approaches, especially those with applications in sectors such as education and information retrieval.

1.3 Summary and Synthesis

Table 1: Summary of Key Literature

Theme	Paper	Methodology	Key Findings	Contribution to Project
Theme 1: Vulnerability Prediction	Hall, O., et al. (2023)	Provides a strategic guide for the prediction model, recommending a hybrid ML/DL approach using multiple "hard" data sources.	Integrative Review of 60 studies on poverty prediction using satellite imagery and machine learning (SIML).	• Models targeting "hard" indicators (e.g., assets) are 17 percentage points more predictive than those targeting "soft" indicators (e.g., income). • Combining ML and DL is 15 percentage points more predictive than DL alone. • Using more datasets significantly increases predictive power.

Theme 1: Vulnerability Prediction	Alturif, G., et al. (2024)	Provides specific technology (1D-CNN) ideal for the project's time-series data (conflict, socio-economic) and the statistical evidence linking poverty to educational disruption.	Implements a 1D-Convolutional Neural Network (1D-CNN) to forecast SDG 1 (No Poverty) [9]. This model is specifically chosen for its ability to analyze time-series data.	• 1D-CNNs can successfully and accurately forecast poverty levels using historical socio-economic data. • Discovered a strong positive correlation (0.84) between SDG 1 (No Poverty) and SDG 4 (Quality Education).
Theme 2: Offline AI Chatbots	Bhosale, V. N., et al. (2025)	Provides a high-performance, cutting-edge option for the chatbot, proving that powerful AI is feasible offline.	Describes the "Echo AI Platform," a system that integrates the LLaMA 3 Large Language Model (LLM) to run in a "completely offline environment".	• The platform delivers "accurate and contextually relevant responses" without internet connectivity. • It prioritizes user data privacy by processing all data locally. • Proves that offline LLMs can be "reliable and robust".
Theme 2: Offline AI Chatbots	**Sahu, A. K., et al.** (2023)	Provides a lightweight, efficient alternative (keyword/hybrid model) that is more feasible for low-resource devices and has a direct, cited	Proposes an "Offline Virtual Chat Bot" using simpler, traditional NLP techniques like "Scripted" (decision tree) and "Keyword	• Highlights the necessity of offline bot for users without reliable internet. • Specifically discusses chatbots for "educational

		application for education.	recognition-predicated" models.	institutions" and as "very potential for education use cases".

1.4 Synthesis of Themes

Theme 1 (Prediction): The paper "Hall et al. (2023)" provides a broad, strategic review of that recommendation of a hybrid ML/DL model that uses a multiple data sources like satellite imagery for the prediction of "hard" indicators of welfare. "Alturif et al. (2024)" provides a demonstration that a 1D-CNN is highly effective for the project's other key datasets such as socio-economic and conflict time-series. This paper also provides the statistical justification for the project's core premise: the 0.84 correlation between poverty and education proves that predicting one can effectively identify the other.

Theme 2 (Support): These two papers: Bhosale et al. (2025) and Sahu et al. (2023), present a clear technological choice. The first one (Bhosale et al. (2025)) represents the high-end, powerful approach in which an offline-capable LLM (LLaMA 3) provides robust, context-aware answers while ensuring data privacy. The second one, Sahu et al. (2023) provides a more lightweight, practical, and efficient alternative proposing simpler keyword or hybrid models which are less resource-intensive and most crucially, are explicitly cited for use in educational settings. This allows this project to make an informed decision, while balancing the power of an LLM against the feasibility of a lightweight model for a low-connectivity, limited-resource environment.

1.5 Conclusion

This literature review has established two key takeaways:

- For vulnerability prediction, a hybrid Machine Learning (ML) and Deep Learning (DL) model is a state-of-the-art approach.
- Offline AI chatbots are viable technology for politically oppressed, war-affected and remote areas.

However, the literature review also reveals a significant gap between the fields of vulnerability prediction and offline aid delivery. The prediction models used in Hall et al., (2023) and Alturif et al., (2024) are academic tools for identification but have an absence of a mechanism to deliver support. Conversely, the chatbot systems used in Bhosale et al., (2025) and Sahu et al., (2023) are reactive tools that depend on a user already having the device and knowledge to use them.

This gap is bridged by this project's primary contribution. It will be the first system to create a single, cohesive framework that uses the output of a vulnerability prediction to proactively guide the deployment of an offline educational and support chatbot, moving beyond academic prediction and creates a practical, end-to-end tool to empower the specific communities in Myanmar which need it most.

2. Data Research

2.1 Introduction

The data research for this project is designed to build an "Offline AI-Powered Community Support and Vulnerability Prediction System for Conflict-Affected Areas in Myanmar", having two main components: a predictive model for at-risk communities' identification and an offline chatbot to provide them with critical support information.

2.2 Research Questions

Two central research questions drive this data exploration:

i. **Which communities are most vulnerable to poverty, food insecurity, health crises, and educational disruption?**
ii. **What specific, actionable guidance on health, education, and livelihood support can be provided to these communities?**

To answer the first question, assumptions cannot help, but to build an accurate predictive model, only exploration and analysis of quantitative, real-world data would help, involving integrating diverse datasets covering conflict, socio-economic factors, and climate risks to identify the key drivers of vulnerability.

For the second question, for the creation of useful support tools, a curate custom dataset from NGO or UN resources is required, necessary to populate the chatbot's knowledge base, ensuring the guidance to provide on health, education, and disaster response accurately and in relevance with the users.

2.3 Organizations

In accordance with the two primary components of this capstone project, the data research findings are organized thematically:

i. **Data for Vulnerability Predication Model**: This section is about the open-source datasets such as conflict, socio-economic and climate, used to train the machine learning model.
ii. **Data for the Offline Chatbot**: This section describes the custom dataset of support information from NGO or UN FAQs, which are required for the chatbot's knowledge base.

2.4 Data Description

Two distinct categories of data will be used in this project:

1. Data for the Vulnerability Prediction Model: This data will be aggregated to create a comprehensive, multi-faceted profile of all regions or townships in Myanmar to identify those most at risk.

<u>Data Sources</u>

Conflict Data: Armed Conflict Location and Event Data Project (ACLED), in this dataset specifically for Myanmar will be used, filtering for event types such as battles, violence against civilians and dates.

Socio- Economic Data: Firstly, from the World Bank Open Data, specifically indicators like "Poverty Headcount Ratio" or "Access to Electricity" and "GNI per capita" at the most granular level available. And secondly from the UNDP Data, the sub-national Human Development Index (HDI) for Myanmar, which includes key indicators for life expectancy (health), expected years of schooling (education) and GNI (Livig standards).

Climate and Environmental Data: NASA Earthdata will be used; specifically:

- VIIRS Nighttime Lights: This will be used as a proxy for economic activity, a "hard" indicator which is recommended in one of the literature reviews.
- GPM (Global Precipitation Measurement): This data will be used to identify areas at high risk for natural disasters like flooding.

<u>Data Format</u>

The data will be collected primarily in CSV and GeoJSON formats, allowing for both statistical analysis in Python with libraries like Pandas and geospatial mapping with libraries like GeoPandas.

<u>Data Size</u>

The final data size is **To be determined** (**TBD**), depending on the final temporal range and geographic granularity of the analysis.

<u>Rationale for Selection</u>

- This multi-source method was adopted since vulnerability is a multifaceted problem that cannot be captured by a single dataset.
- ACLED gives a direct, quantifiable estimate of the project's "conflict-affected" component.
- The World Bank and UNDP data offer the "ground truth" socioeconomic indicators required to train the model to spot patterns of poverty, health crises, and educational disruptions.
- NASA provides powerful "hard" indicators (nighttime lighting, climatic risk), which have been demonstrated in the literature to be highly predictive of welfare (e.g., Hall et al.).

2. Data for the Offline Chatbot Knowledge Base: This dataset will be built from scratch, as no single, pre-existing database exists for this specific purpose.

Data Source

This will be a custom-curated dataset. The data will be gathered from publicly available FAQs, guidelines, and reports from authoritative bodies, such as:

- UNICEF Myanmar (Education and Child Health)
- World Health Organization (WHO) (for health emergencies)
- UNESCO (for educational resources)
- Other relevant non-governmental organizations (NGOs) and United Nations agencies providing relief in Myanmar.

Data Format

The data will be organized in a simple JSON or CSV file with question-answer pairings (e.g., {"question": "How to get food aid?", "answer": "...") or topically grouped help. This format is lightweight and may be parsed by a rudimentary chatbot.

Data Size

The initial target size will be around 200-500 high-priority entries. The database's size must be maintained minimally and efficiently so that it may be stored locally on low-resource, offline devices (for example, a basic smartphone).

Rationale for Selection

- This bespoke dataset is critical because the project's purpose is to provide "help on accessing NGO and UN support services". This data is not pooled anywhere else.
- It is directly related to the project's support goals of "health, education, livelihood, and disaster response".
- By collecting material from official UN/NGO websites, we ensure that the chatbot's responses are accurate, safe, and actionable for vulnerable end users.

2.5 Data Analysis and Insights

The data analysis plan will address both the quantitative vulnerability data and the qualitative chatbot data to uncover the necessary insights for the project.

First, the analysis of the vulnerability prediction data will focus on identifying key patterns and predictive drivers. The primary dataset will be a merged table where each row represents a geographic unit (e.g., a township in Myanmar) and the columns represent the different data points (conflict, socio-economic, climate).

Descriptive Statistics: We will calculate descriptive statistics (mean, median, standard deviation) for our key variables, such as **conflict_events_per_month** (from **ACLED**),

poverty_headcount_ratio (from **World Bank/UNDP**), and **avg_nighttime_light** (from **NASA VIIRS**). This will establish a baseline understanding of "normal" vs. "extreme" values.

Visualizations and Insights: Two main visualizations will be created:

- **A Geospatial Heatmap** using GeoJSON and ACLED data to instantly reveal the geographic "hotspots" of conflict.
- **A Correlation Matrix**, similar to the one in the Alturif et al. paper, to statistically identify the strongest relationships between variables (e.g., conflict_events, poverty_rate, avg_nighttime_light).

The key insights from this quantitative analysis will be the identification of the most powerful predictive variables and the specific regions most at-risk.

Second, the analysis of the offline chatbot data will be qualitative and structural. This dataset is a custom knowledge base of text.

Pattern Analysis: The raw information from NGO/UN sites will be analyzed and "themed." We will group all questions and answers into primary categories.

Key Insight: The main insight from this analysis will be the final, structured knowledge base for the chatbot. We anticipate discovering the following main themes:

- Health Services (e.g., "Where is the nearest clinic?")
- Educational Resources (e.g., "How to access offline learning materials?")
- Food and Livelihood Aid (e.g., "How to register for food distribution?")
- Emergency/Disaster Response (e.g., "What to do in a flood?")

2.6 Conclusion

The data research yielded two key discoveries. First, a strong, multi-source data strategy for the vulnerability model is possible. By combining conflict data (ACLED), socioeconomic data (World Bank/UNDP), and environmental data (NASA), we may build a full vulnerability profile. The planned research, which includes geospatial heatmaps and correlation matrices, will reveal the precise risk drivers and pinpoint the most vulnerable areas.

Second, a defined strategy for the chatbot's knowledge base has been developed. We can construct a lightweight, accurate, and practical information tool for health, education, and livelihood support by collecting a custom dataset from credible NGO and UN sources.

The importance of these findings to the project's overall goals is paramount. This data plan provides the essential foundation for both components of the project. Quantitative data makes the predictive model possible, and the qualitative dataset provides the core value for the offline support tool. This data research confirms that the project's objectives are achievable.

3. Technology Review

3.1 Introduction

This project's hybrid design requires two distinct and specialized technology components. The first is a Machine Learning (ML) or Deep Learning (DL) model capable of analyzing diverse datasets (socio-economic, conflict, satellite) to predict vulnerability. The second is a Natural Language Processing (NLP) chatbot system designed to function in "low-connectivity environments" to deliver aid and educational resources.

A thorough technology review is of critical importance because the project's success hinges on selecting tools that are not only powerful but also practical for the intended environment.

For the prediction model, the technology must be accurate, interpretable, and capable of handling complex, time-series data.

For the offline chatbot, the technology choice is even more constrained. It must be efficient, reliable without internet access, and lightweight enough to run in "low-resource, conflict-affected settings".

This review will therefore evaluate and compare the leading technological options for both components to justify the final architecture for this project.

3.2 Technology Overview

1. Technology for Vulnerability Prediction

This project requires a model that can analyze historical, structured datasets (e.g., CSVs of conflict and economic data) to predict future risks. The literature review identified two primary approaches: traditional Machine Learning (ML) and more recent Deep Learning (DL) models.

Technology Option A: Machine Learning (e.g., Random Forest)

Purpose: Random Forest is a supervised learning algorithm used for classification and regression. Its purpose is to learn rules from a set of input features (e.g. conflict rates, poverty data) to make a prediction (e.g., "high vulnerability" or "low vulnerability").

Key Features: It is an "ensemble" method that works by building hundreds of individuals "decision trees" during training. The final prediction is made by taking the majority vote (for classification) or average (for regression) of all the trees. This makes it highly accurate, robust to outliers, and less prone to overfitting than a single decision tree.

Common Use: As noted in the project proposal and supported by the literature review (which identifies ML as a primary tool), these models are commonly used for poverty prediction. They are particularly well-suited for handling diverse, structured data tables, such as the planned ACLED and World Bank datasets.

Technology Option B: Deep Learning (e.g., 1D-Convolutional Neural Network)

Purpose: A 1D-CNN is a type of deep learning model specifically designed to find complex patterns in sequential data, such as time-series.

Key Features: Unlike models that look at data points individually, a 1D-CNN applies "filters" to "efficiently extract temporal correlations" from historical data. This allows it to learn from trends over time (e.g., a "sudden increase in conflict" followed by a "drop in economic indicators").

Common Use: This technology is used for advanced time-series forecasting. The Alturif et al. (2024) paper uses it precisely for this project's goal: to "project future performance" of SDG 1 (No Poverty) by analyzing 22 years of historical socio-economic data.

2. Technology for Offline Chatbot Systems

This project requires a system that can understand user queries and provide pre-defined answers from a local knowledge base, all "without the need for internet connectivity" .

Technology Option A: Large Language Models (LLMs)

Purpose: The purpose of this technology is to provide highly accurate, context-aware, and human-like conversational AI in an offline environment.

Key Features: As described in the Bhosale et al. (2025) paper, a model like LLaMA 3 is pre-trained on a massive dataset, giving it advanced natural language understanding. The key feature is its ability to be "optimized to work offline" and run on a local device. This ensures that user interactions "remain within the user's local environment," which provides high data privacy and security.

Common Use: This technology is used to build sophisticated, offline conversational agents (like the "Echo AI Platform") for secure information retrieval, "especially valuable in industries such as healthcare, education, and emergency services".

Technology Option B: Lightweight NLP / Keyword-Based Models

Purpose: The purpose of this technology is to provide a simple, efficient, and reliable way to retrieve information from a custom knowledge base, specifically for low-resource devices.

Key Features: This approach is simpler than an LLM. A "Scripted" or "Quick Response" bot uses a "hierarchical decision tree" to guide the user to an answer. A "Keyword recognition-predicated" bot is "programmed to listen to what the user is typing" and match those terms to pre-defined answers in its local database.

Common Use: As described by Sahu et al. (2023), these lightweight models are ideal for "CHIT CHAT BOT" applications that must work offline. They are frequently used for specific-domain questions, and the literature explicitly identifies them as being "very potential for education use cases" and for use in "educational institutions"

3.3 Relevance to the Project

1. Relevance of Prediction Model Technology

The technologies for vulnerability prediction are directly relevant because they provide a proven, data-driven method for answering the project's first research question: "Which communities are most vulnerable?".

- How they address challenges: Our project needs to analyze complex, multi-source data (conflict, socio-economic, climate).
- The Random Forest model is relevant because it is highly effective at handling diverse, structured data tables and is known for its high accuracy and interpretability.
- A 1D-CNN is particularly relevant because your ACLED (conflict) and UNDP (socio-economic) data are time-series. This model is specifically designed to "efficiently extract temporal correlations" from this exact kind of data.
- How they contribute to success: Using these models, particularly in a hybrid approach as suggested by Hall et al. (2023), will allow the project to move beyond simple assumptions and create a statistically validated map of vulnerability. This directly contributes to the project's goal of enabling "data-driven interventions".

2. Relevance of Offline Chatbot Technology

The chatbot technologies are relevant because they directly address the "low-connectivity environment", which is the core technical challenge of the project's support component.

- How they address challenges: The primary challenge is providing reliable information "without the need for internet connectivity".
- Both LLM-based and lightweight NLP models solve this. They are designed to run entirely locally, processing user queries and retrieving answers from a local knowledge base.
- This offline capability is crucial for ensuring data privacy and security, as all user interactions "remain within the user's local environment".
- How they contribute to success: These technologies are the only way to achieve the project's goal of providing "direct community support". They are the mechanism for delivering the curated NGO/UN guidance on health, livelihood, and education, as both technological options are cited as "especially valuable" or "very potential" for educational and emergency use cases.

3.4 Comparison and Evaluation

Table 2. Comparison of Vulnerability Prediction Models

Factor	Machine Learning (Random Forest)	Deep Learning (1D-CNN)
Strengths	• Highly effective for structured, tabular data (like the planned CSVs). • More "interpretable," allowing us to see which factors (e.g., conflict vs. poverty) are the most important predictors. • Generally efficient and faster to train.	• Specifically designed for time-series data; can "efficiently extract temporal correlations" (e.g., how a conflict event over time affects poverty). • Proven to be highly accurate in forecasting SDG 1 (No Poverty) using historical data. • Literature finds that combining ML and DL yields the best predictive power.
Weaknesses	• Not specifically designed for sequential or time-series data; may miss temporal patterns.	• Less interpretable (a "black box"); it is harder to explain *why* it made a specific prediction. • More computationally expensive and complex to train than a Random Forest.
Suitability	**Very High.** It is the most suitable technology for the *time-series* aspect of the project's data (e.g., economic trends, conflict rates over time).	**High.** It is an excellent, "interpretable" choice for the structured data (World Bank, ACLED). It serves as a perfect baseline and is a core part of a hybrid model.

Evaluation: A hybrid approach combining both technologies is the most suitable, as recommended by Hall et al. (2023). We can use a Random Forest for static satellite and asset indicators and a 1D-CNN to analyze the temporal data from ACLED and the UNDP.

Table 3: Comparison of Offline Chatbot Technologies

Factor	Large Language Models (e.g., LLaMA 3)	Lightweight NLP / Keyword Models
Strengths	• High Performance: Delivers "accurate and contextually relevant responses". • Advanced NLU: Can understand complex, human-like queries. • High Privacy: All processing is local, ensuring data security.	• Low Cost & Ease of Use: Simpler to implement and maintain. • High Scalability: Very "lightweight" and can run on minimal, low-resource devices (basic smartphones). • Fast: Retrieves pre-defined answers instantly. • Proven Use Case: Specifically cited as "very potential for education use cases".
Weaknesses	• **High Cost:** Requires significant computational resources (RAM, processing power) to run, making it unsuitable for "low resource" devices. • **Large Size:** The model itself is very large, making deployment difficult.	• Low Performance: Not "smart." It cannot answer questions outside of its pre-defined script. • Limited NLU: Relies on basic keyword matching and cannot understand complex user intent.
Suitability	**Low.** While powerful, the "high cost" (computational, not monetary) makes it impractical for deployment in "low-resource, conflict-affected settings" where users may not have high-end devices.	**High.** This technology is the most suitable. Its "low cost" (resource footprint), "ease of use," and "scalability" are perfectly aligned with the project's real-world constraints. It is the most feasible way to deliver the necessary aid and educational information.

Evaluation: A Lightweight NLP / Keyword Model is the chosen technology for the chatbot. The project prioritizes accessibility and feasibility over conversational power.

3.5 Use Cases and Examples

This section provides real-world use cases and examples of how the reviewed technologies have been applied, drawing directly from the literature.

Vulnerability Prediction (ML/DL)

- Hall, O., et al. (2023): This review itself is a collection of 60 use cases where researchers have successfully applied ML and DL (like CNNs) to satellite imagery to predict poverty and welfare.
- Alturif, G., et al. (2024): This paper provides a direct case study of using a 1D-CNN to forecast SDG 1 (No Poverty) scores for five countries. This is a real-world example of the exact methodology planned for this project's prediction model.

Offline Chatbot Systems (NLP)

- Bhosale, V. N., et al. (2025): This paper presents the "Echo AI Platform" as a case study. It is a system built with LLaMA 3 to provide offline, secure information retrieval for industries like healthcare, education, and emergency services. This demonstrates that high-powered offline AI is a current, real-world technology.
- Sahu, A. K., et al. (2023): This paper proposes a "CHIT CHAT BOT" specifically for offline use. It provides the direct use case of applying such bots as "educational tools" and for use in "educational institutions", which directly supports this project's goal of delivering educational resources.

3.6 Research Gaps and Opportunities

The technology review identified a significant gap which this project is uniquely positioned to fill.

The Gap in Literature: The literature shows a clear separation between prediction and action.

The vulnerability prediction models (per Hall et al. and Alturif et al.) are primarily academic tools for identification. They are designed to "statistically analyze literature" or "project future performance", but they do not include a mechanism to deliver support to the populations they identify.

The offline chatbot systems (per Bhosale et al. and Sahu et al.) are reactive tools. They are valuable, but they rely on a user to already possess the tool and know how to ask for help . They do not proactively target at-risk communities.

This Project's Opportunity (Contribution): This project's main research opportunity is to bridge this gap by creating a single, end-to-end "hybrid design". This project will be the first (to our knowledge) too:

- Use a vulnerability prediction model to identify at-risk regions.
- Use that output to proactively guide the deployment of the offline support chatbot to those specific communities.

This moves technology from passive analysis to active, data-driven intervention, which is a novel contribution to the field.

3.7 Conclusion

This technology review has yielded several key takeaways that confirm the project's technical feasibility.

Key Takeaways (Prediction): For vulnerability prediction, the literature shows that a hybrid ML/DL model is state-of-the-art. The 1D-CNN (from Alturif et al.) is an ideal technology for our time-series data, while Random Forest (from the proposal) is a robust tool for our structured data.

Key Takeaways (Chatbot): For the offline chatbot, the review presented a clear trade-off between the high-performance LLaMA 3 model and a lightweight keyword-based model.

Based on the "**Comparison and Evaluation**", the chosen technology for the chatbot is the lightweight NLP/keyword model (per Sahu et al.). While an LLM is powerful, its high computational "cost" and large size make it unsuitable for the project's "low resource" constraints. The lightweight model's "ease of use," "scalability," and proven application in education make it the most appropriate and beneficial choice.

This technology review confirms that the tools for this project exist. The chosen technologies (a hybrid ML/1D-CNN model and a lightweight NLP chatbot) are perfectly balanced to provide high predictive accuracy while ensuring that the final support tool is feasible to deploy in the real-world, low-connectivity environments of Myanmar.

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