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Pathshala.ai: An Offline Bangla Language Model for High School Education in Bangladesh

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Pathshala.ai: An Offline Bangla Language Model for High School Education in Bangladesh

A Thesis submitted to the Institute of Information and Communication Technology, Shahjalal University of Science and Technology, in partial fulfillment of the requirements for the degree of B.Sc.(Eng.) in Software Engineering.

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Recommendation of the Thesis Supervisor

To Whom It May Concern

This letter is to certify that, the thesis entitled **Pathshala.ai :An Offline Bangla Language Model For High School Education in Bangladesh** undertaken by the students **Abrar Masud Nafiz** and **Hamim Rahman** is under my supervision. I, hereby, agree that the thesis can be submitted for examination.

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Approval of the Thesis

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Thesis Title: Pathshala.ai: An Offline Bangla Language Model For High School Education in Bangladesh

This is to certify that the above mentioned thesis, submitted by the students named above in **November, 2024** as part of the requirements of the course **SWE 450**, is being approved by the Software Engineering, Institute of Information and Communication Technology as a partial fulfillment of the B.Sc.(Eng.) degrees of the above students.

Director of IICT	**Supervisor**
Prof Mohammad Abdullah Al Mumin	Dr. Ahsan Habib
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Abstract

In Bangladesh, the educational disparity between urban and rural areas persists, leaving many high school students in remote regions without access to a personal tutor for simple problems. This thesis presents the development of Pathshala.ai, a computationally efficient Bangla language model designed as an offline personal tutor for high school students. Pathshala.ai addresses the unique linguistic challenges of the Bangla language while aligning with the curriculum of classes 6-10. The model leverages advanced transformer-based architectures, optimized through sparse attention mechanisms and quantization, to function on low-resource devices common in rural settings.

The research details the curation and preprocessing of high school-level educational content tailored for Bangla, ensuring relevance and coherence in generated text. Additionally, lightweight embeddings specific to the Bangla language streamline tokenization and processing. The model's effectiveness is evaluated through comparative benchmarking focusing on response accuracy, educational effectiveness, and computational efficiency. Pathshala.ai demonstrates significant potential to bridge educational gaps and serve as a stepping stone toward inclusive, technology-driven learning solutions for Bangladesh's high school students.

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Chapter 1

Introduction

1.1 Research Background

There are many more issues that are part of the Bangladeshi education system. In rural areas, the problem of education is usually not noticed because of a lack of access to quality educational services. Students living in urban areas do not face this situation. In urban areas, students have several helping hands, like better private tuition, the use of the internet, and various digital tools that help in their development. In rural areas, students suffer several disadvantages due to lack of resources or infrastructure. This educational disadvantage creates a poor education system and hampers the development of the nation as well.

This technological development has made the buying of cheap smartphones or smart devices rather easier in the recent era. The increasing availability of cheap smartphones and access to the internet in rural Bangladesh is, therefore, an opportunity to narrow these gaps. Such technological advancements can provide a way to make the creation of learning resources more computationally tractable for rural settings. Bangla is a language spoken by more than 230 million people on earth, with unique articulacy and textual equipment given to its rich syntax, morphology, and

phonetic structure. Recently, massive language models like BERT and GPT have been the game changer for NLP studies, while most language-specific model designs are oriented with nuances in the English language only. The absence of special-purpose Bangla models restricts the possibility of creating tools targeted at the needs of the Bangla-speaking learners [Hasan et al., 2022]. A model in the Bangla language, for the curriculum at the high school level, and working on the low-resource, cheap hardware offline, will help make a difference in rural schools and beyond.

1.2 Problem Description

The major ills the rural education system of Bangladesh suffers from are:

- **Scarce Resources**: Most of the rural schools and institutions can barely afford enough trained or experienced teachers, adequate course materials, and sometimes even an appropriate access to the Internet.
- **Inadequacy of Bangla-Oriented Digital Tools**: Most digital learning tools focus on, and seem to give more importance to, the usage of the English language rather than other languages.
- **High Computation Costs:** Current NLP models are computationally intensive to run and thus cannot work on low-cost devices common in rural areas.

Such challenges urgently require a lightweight, efficient, and customized solution for the Bangla-speaking learners in a limited resource setting. This needs to be a solution which is easy on the complex Bangla linguistic aspects and effortlessly operates on low-powered devices such as entry-level smartphones or laptops. In light of recent breakthroughs in transformer-based models, along with transfer learning and pruning, one can construct a model to provide accurate, curriculum-aligned suggestions that are not dependent on local computation resources. It's just another critical model development that would unblock barriers in access to quality education

for rural Bangladeshi students and enable them to do more self-learning rather than dependent learning from private tutors. This is in line with global trends in developing resource-efficient, localized technologies for addressing systemic inequities across education systems. [UNESCO, 2020, UNDP, 2021].

1.3 Objectives

Our research therefore seeks to meet the needs of rural Bangladeshi students through the development of an easy-to-use and accessible digital learning tool for students at the high school level that is effective in its purpose. The key objectives of our research are mentioned below:

• The Bangla language model specialisation is developing a Lightweight, Bangladeshi curriculum-focused Bangla language that will help the students mainly in higher secondary level mathematics science, social science, etc,. Unlike any other models, This model understands and generates results aligned with Bangladeshi NCTB (National Curriculum and textbook board) books and creates relevant content which students grasp easily.

• Optimize for Low Resource Devices: Ensure the Bangla language model can run efficiently on low processing power or resource-low devices to ensure accessibility in the rural areas of Bangladesh.

• Evaluate Effectiveness and Performance: The effectiveness and overall performance of the model will be gauged with other Large Language Models. Not only is the accuracy of the model in answering questions important but also how it helps students in their curriculum activities. Metrics to be measured are power consumption and resource utilization.

The feedback would come directly from the students going to use the system: whether efficient, easy to use; what works and what doesn't work. The ultimate aim

was to provide an intuitive useful digital teacher offering pupils a fair opportunity of learning and developing even in challenging circumstances.

1.4 Research Significance

This paper presents a language model, Pathshala.ai, which is intended for Bangladeshi high school students. Complementary to the global goals, such as UN's SDG 4-quality education-this model will contribute its part by providing access to quality educational resources. Additionally, this would set a model for developing lightweight NLP solutions applicable in other low-resource languages, thus helping global efforts in educational technology.

The design principles of the model, focusing on linguistic diversity and computational limitations, scale easily to other underserved regions and solve similar disparities all over the world.

1.5 Thesis Structure

This thesis is organized in the following manner:

- **Chapter 2: Technical Foundations** - The theoretical foundations of Natural Language Processing (NLP), with a focus on transformer architectures, challenges associated with the Bangla language, and their relevance to educational applications.
- **Chapter 3: Model Design and Implementation** - The design methodology, the process of data collection, preprocessing procedures, and the training and optimization of the model.
- **Chapter 4: Evaluation and Comparative Analysis** - The deployment

framework, testing protocols, benchmarking results, and comparisons of the model's performance against existing solutions.

- **Chapter 5: Future Work** - Potential extensions of the model to additional domains, languages, and features.
- **Chapter 6: Conclusion** - A summary of the research findings, recognition of limitations, and a roadmap for future advancements.

Chapter 2

Technical Foundations

2.1 Intro to Language Models

Language models are the fundamental tools of NLP, allowing machines to understand and interact with human languages by providing an ability to produce, understand, and generate various contents. It has thus been very essential in a number of different applications, including translations, summarizing, and question answering by estimating the probability of the next word sequences. While earlier these models relied on statistical methods, the introduction of deep learning and neural networks has revolutionized the field of natural language processing in particular with the advent of transformer architectures such as BERT by Devlin et al. [2019] and GPT by Brown et al. [2020]. Transformer architectures are an offshoot of neural networks, and indeed very good for sequential data processing due to their self-attention mechanisms, which allow them to find complex patterns and relationships in text.

It has completely revolutionized NLP with the raising of new bars on standards pertaining to accuracy and adaptability across various tasks. But its resource-intensive nature is a challenge for us to adapt it in low resource and cost-effective devices while having the efficiency to be better.

2.2 Transformer Architectures

Vaswani et al. [2017] introduced the transformer architecture, one of the most revolutionary concepts in natural language processing. The title of the paper reads "Attention Is All You Need," which has since become the cornerstone of almost all large language models.

Here is what makes transformers special:

- **Self-Attention Mechanism**: The model is capable of relating each word to how important it is considered relative to other words in a sentence. For example, here between "cat" and "friendly," both words can be related even if other words intervene in that sentence.

- **Positional Encoding**: Machines do not understand word order the way humans do, but positional encoding is given to each word as a "place," so the model knows what order things go in within a sentence.

- **Parallel Processing**: Unlike older models, which processed one word at a time, transformers process whole sentences all at once. This brings a significant increase in training speed and better results because context can be understood holistically.

- **Scalability**: Transformers can scale up to handle vast datasets, making them ideal for training large models like OpenAI's GPT and Google's BERT.

However, this power comes at a certain cost: transformers are very expensive in computational terms, requiring a lot of memory and processing capability. This remains an enigma during systems design for under-resourced areas, such as in rural communities. Several recent efforts have focused on making lightweight versions of transformers that are much more efficient but at somewhat lower accuracy, such as MobileBERT by Sun et al. [2020] and DistilBERT by Sanh et al. [2019].

Adaptation of these innovations can help make the models more accessible to users in low-resource environments and can help bridge the gap between the latest technology and reality.

2.3 Challenges of Bangla in NLP

There is rich diversity in Bangla as from millions of people, but such features once added to the richest of all, add to his/her unique place of making NLP tools. There are some prime challenges below:

- **Complex Word Forms (Morphology)**: Morphologically, a single word changes its form according to tense, gender, number, and context in Bangla language. The example of this would be the word meaning "to write"—*likhi*, becomes *likhona*, *likhtechi*, or *likhini* according to its usage and context. Such a great number of word alterations makes it difficult for models to understand and predict them.

- **Flexible Sentence Structure**: Sentences in Bangla can have other arrangements other than fixed order. For example, "I went to the market yesterday" would be expressed in Bangla with possible different structures:

  - *Ami kal bajar e giyechilam.*
  - *Kal ami bajar e giyechilam.*

  Variability makes parsing and accurate generation of such sentences by the model a more tasking thing.

- **Less Data (Sparse Resource)**: Bangla has only a handful of annotated datasets unlike in the case of English where voluminous data is available for training. As a result of this, it becomes difficult to develop models which can work well for tasks of translation, summarization, and question answering.

- **Reliance on English-Centric Models**: Train many NLP models mostly in English first, and then it goes to fine-tune other languages. However, most of these, based on a typical English model, do not work really well without supplementary customization and data because of the uniqueness of grammar, vocabulary, and idioms of Bangla.

These concerns have been dealt with instruction specific Bangla tools such as Bengali-BERT [Sarker et al., 2020], which fine-tune existing models with Bangla data. While this is promising, it would take a long time before accurate and practical models could be situated for Bangla, especially for specialized fields such as education.

2.4 Educational Applications of NLP

Natural Language Processing (NLP) will be transforming the very fabric of education—from making education more interactive and personalized to having an element of one-on-one tutoring, automatic grading, and creating tools for learning new languages. Personalized sequences of explanations can now be provided by AI systems through NLP for students, just like a private tutor would teach. Examples of how parents and students can learn using an NLP-enabled application are Duolingo, which uses NLP for language learning by correcting users' mistakes and giving feedback, and IBM Watson, which is available for personalizing the learning paths of students in some educational applications [Dhiban et al., 2021].

In the contexts of rural Bangladesh, education is less than ideal and limited; herein lies the importance of NLP tools in transforming learning. They have the potential to do the following:

- Bangla learning materials to deliver lessons conforming to the school curriculum.
- Work without Internet, which is a major constraint for areas that have not been connected to the Internet.

- Enable the autonomous learning of students, making expensive private tuition less necessary.

Creation of such tools for the high school subject areas in Bangla will pave the way in removing the education gap especially in the underprivileged areas. The students will also then become less enslaved to the teacher's supervision or sound internet connectivity.

2.5 Features of Requirement Need for Lightweight and Efficient Models

It would require efficient and lightweight models performing well since equal and stable access is not provided to powerful devices in rural areas. By applying certain size and resource reduction techniques, NLP models are thus kept very light and yet not a superficial performance. The three critical approaches are:

- **Knowledge Distillation**: For a big, complicated model (named the teacher or teacher model), one usually creates a much scaled down, simpler version of that model called the student model. The student model learns from the teacher but retains most of the performance while requiring far fewer resources [Hinton et al., 2015].

- **Quantization**: Quantization simply reduces precision of the numbers used in a model's calculations. A model, for instance, might now be using 8-bit precision instead of the conventional 32-bit. Obviously, this leads to reduced computational power requirement, and hence the model becomes faster and energy efficient [Jacob et al., 2018].

- **Pruning**: It prunes portions of a model which have less contribution in the overall performance of the model. By pruning these unnecessary layers or pa-

rameters, the model will become lighter and easier to run especially on low-resource devices [Han et al., 2015].

Thus, lightweight models such as Pathshala.ai could afford quality education to rural students under those difficult conditions but using cheaper devices to run smoothly and efficiently.

2.6 Summary

This chapter explained foundational needs for a rural education-centered Bangla language model. The extensive discussions included the contribution of the transformer architectures, the applicability challenge of processing Bangla, and the motivational aspects of building efficient models. The work includes applying advanced techniques to provide solutions through knowledge distillation, quantization, and pruning. This research attempts to ensure proper training of models using very few resource consumptions.

Chapter 3

Model Design and Development

Introduction

This chapter discusses the design and development of **Pathshala.ai**, an offline Bangla language model tailored to meet the educational needs of high school students in Bangladesh. The chapter covers the - a) architectural framework, b) data preparation methodologies, c) training strategies and d) optimization techniques that ensure the model's efficiency and efficacy in a resource-limited environment.

3.1 Model Architecture

Transformer-Based Framework

We're using the transformer-based architecture introduced by Vaswani et al. (2017) [Vaswani et al., 2017], which is renowned for its self-attention mechanisms that excel in capturing long-range dependencies and contextual relationships. This makes it suitable for language modeling tasks in a linguistically rich language with complex structures like Bangla.

Step	Description	Output
1	Input Sentence	বাংলাদেশে শিক্ষার মানোন্নয়নে প্রযুক্তির ব্যবহার ক্রমবর্ধমান গুরুত্বপূর্ণ হয়ে উঠছে
2	BPE Regex Pre-tokenization	Tokens are split based on BPE regex rules
3	Tokens	['বাংলাদেশে', 'শিক্ষার', 'মানোন্নয়নে', 'প্রযুক্তির', 'ব্যবহার', 'ক্রমবর্ধমান', 'গুরুত্বপূর্ণ', 'হয়ে', 'উঠছে']
4	Check Morph Table?	Decision to check if morph decomposition is needed
5a	Morph Decomposition	'মানোন্নয়নে' → ['মান', 'উন্নয়ন', 'নে']
		'গুরুত্বপূর্ণ' → ['গুরু', 'ত্ব', 'পূর্ণ']
5b	BPE Tokenizer	Tokenizes using standard BPE rules
6	Output Tokens	['বাংলা', 'দেশে', 'শিক্ষা', 'মান', 'উন্নয়ন', 'নে', 'প্রযুক্তি', 'ব্যবহার', 'ক্রম', 'বর্ধ', 'মান', 'গুরু', 'ত্ব', 'পূর্ণ', 'হয়ে', 'উঠছে']
7	Final Tokenization Output	Processed tokens ready for downstream tasks

Figure 3.1: Morphology Aware Tokenization

Customizing for Bangla Linguistics

Bangla's agglutinative nature and intricate syntax required tailoring the transformer architecture for enhanced compatibility:

- **Morphology-Aware Tokenization:** Byte Pair Encoding (BPE) is used to handle Bangla's complex word formations by breaking them into manageable subword units.
- **Context-Sensitive Embeddings:** Custom embeddings, with an embedding size of 768, capture the phonetic and script-specific nuances of Bangla.
- **Syntax-Conscious Positional Encoding:** Adjustments to positional encoding account for Bangla sentence construction and word order.

Efficiency Considerations

To enable smooth operation on low-resource devices:

- **Layer Reduction:** The model uses 12 encoder layers instead of the standard 24.
- **Parameter Compression:** Techniques such as weight sharing reduced the total parameter count.
- **Sparse Attention:** Sparse attention mechanisms focus computational resources on significant tokens, reducing overall complexity.

Components Breakdown

1. **Embedding Layer**
    - Lightweight embeddings customized for Bangla enable effective handling of morphology and semantics.
    - Subword tokenization reduces vocabulary size, improving computational efficiency.
2. **Encoder Layers**
    - The model includes 12 layers with multi-head attention and feed-forward networks, striking a balance between performance and computational overhead.
3. **Attention Mechanism**
    - Sparse attention with 12 heads improves focus and reduces unnecessary token computations.
4. **Output Layer**
    - The final layer maps internal representations to vocabulary outputs, ensuring contextually accurate and curriculum-aligned responses.

3.2 Data Collection and Preprocessing

Data Sources

The dataset was meticulously assembled from a diverse range of authoritative educational materials, ensuring both breadth and depth in content coverage. Below, the primary sources are detailed.

1. **Curriculum Textbooks**

• **Comprehensive Extraction:**

The core dataset was systematically curated from the official national curriculum textbooks for Classes 6–10. This approach guaranteed the inclusion of all foundational concepts, definitions, theories, and prescribed explanations, providing a robust foundation aligned with national educational standards.

• **Subject Coverage:**

To ensure comprehensive subject matter representation, the dataset encompassed key disciplines such as Mathematics, Science (subdivided into Physics, Chemistry, and Biology), Social Studies, Language Arts (Bangla and English), and Religious Studies. This interdisciplinary focus supports the creation of a well-rounded dataset reflective of the entire curriculum.

• **Edition Consistency:**

Only the latest textbook editions were utilized, ensuring relevance and alignment with recent updates to the curriculum. This consistency reinforces the dataset's applicability to current educational directives.

• **Annotation of Key Concepts:**

Significant learning objectives and core concepts were annotated to facilitate targeted learning and streamlined data retrieval for model training and interactive use.

2. **Online Educational Platforms**

• **Integration of Shikkhok Batayon Resources:**

Materials such as multimedia lessons, illustrative examples, problem sets, and ex-

planatory videos sourced from *Shikkhok Batayon* were incorporated. These resources added a contemporary pedagogical dimension to the dataset, aligning it with students' diverse learning preferences.

• **BanglaWiki Database Utilization:**

Encyclopedic entries, historical data, and scientific explanations from *BanglaWiki* enriched the dataset, offering real-world context to curriculum-based topics and fostering deeper comprehension.

• **Insights from Blogs and Forums:**

Credible educational blogs, teacher forums, and online discussions were referenced to provide multiple explanatory approaches for complex topics. This inclusion aimed to mirror diverse instructional methodologies and learning strategies.

• **Verification of Online Resources:**

All online resources underwent rigorous verification processes to ensure alignment with curriculum standards, credibility, and accuracy.

3. **Auxiliary Content**

• **Supplementary Workbooks and Practice Materials:**

Additional workbooks and exercises were integrated to include practical applications, problem-solving activities, and exercises promoting analytical skills development.

• **Past Examination Papers:**

The dataset incorporated previous years' examination papers to provide insights into assessment styles, question complexity, and format. These elements prepare the model for generating assessment-specific responses.

• **Subject-Specific Articles and Journals:**

Relevant scholarly articles, educational journal entries, and research publications supplemented the dataset with advanced insights and up-to-date information.

• **Official Publications:**

Government-issued educational materials, such as policy documents and curriculum guidelines, were reviewed and incorporated to align the dataset with national educational objectives.

• **Multimedia Content:**

Diagrams, charts, and infographics were digitized and annotated to support varied learning styles, with a focus on enhancing visual engagement.

Data Curation and Filtering

Relevance Filtering:

• **Content Alignment:**

Advanced filtering mechanisms and manual reviews were employed to remove irrelevant and outdated information, ensuring that the dataset remained strictly aligned with the prescribed curriculum.

• **Elimination of Redundancy:**

Redundant and duplicate entries were identified and removed to enhance dataset efficiency and ensure unbiased training.

• **Cultural Sensitivity:**

Content was reviewed to ensure inclusivity and respect for local norms, safeguarding against cultural insensitivity or bias.

Accuracy Verification:

• **Expert Validation:**

Input from subject matter experts and experienced educators was sought to verify the accuracy and reliability of the content. This collaborative effort enhanced the dataset's overall quality.

• **Cross-Referencing with Standards:**

Content was cross-checked against official curriculum guidelines and credible sources to uphold educational integrity.

• **Plagiarism Detection:**

Advanced tools ensured the originality of content, preventing copyright violations and intellectual property issues.

Quality Assessment:

• **Readability Analysis:**

The dataset was reviewed for language appropriateness, ensuring suitability for the targeted student demographics.

• **Standardization:**

Consistent formatting and terminology were maintained throughout the dataset to avoid confusion.

• **Iterative Feedback Incorporation:**

Feedback from educators and students was incorporated iteratively to refine the dataset's effectiveness.

Preprocessing Steps

Text Cleaning:

• Removal of extraneous symbols, formatting artifacts, and irrelevant characters ensured clean data for processing.

• Automated tools rectified spelling errors and grammatical inconsistencies.

• Uniform formatting, including punctuation and capitalization, facilitated consistent parsing.

Tokenization:

• Subword tokenization (using Byte Pair Encoding) was implemented to manage complex morphological structures and enhance the model's vocabulary handling.

• Sentence segmentation ensured logical coherence within the dataset.

Normalization:

• Spelling variations, synonyms, and regional dialects were standardized to a uniform curriculum-approved form.

• Unicode normalization ensured consistent representation of special characters

and diacritics.

Lemmatization and Stemming:

• Words were reduced to their root forms using morphological analysis, aiding in dimensionality reduction.

• Part-of-speech tagging was employed to enrich syntactic information.

Stop Word Removal:

• Common stop words were selectively removed to emphasize informative content while preserving context.

Data Formatting:

• The dataset was structured into machine-readable formats (e.g., JSON or XML), with metadata such as subject tags and source references added to enhance functionality.

Challenges and Solutions

1. **Data Scarcity:**

Augmentation techniques such as paraphrasing, back-translation, and collaboration with educators were used to mitigate data shortages. Open educational resources were also leveraged ethically to expand the dataset.

2. **Dataset Imbalance:**

Stratified sampling, oversampling of minority classes, and weighted loss functions addressed class imbalances. Ongoing monitoring ensured proportional representation over time.

3. **Language Complexity:**

Multilingual support modules and idiomatic repositories were developed to handle dialectal variations, special characters, and script-specific nuances.

4. **Technical Constraints:**

The pipeline was optimized for scalability, with modular design and hardware accelerators like GPUs used to manage computational demands.

5. **Ethical and Legal Considerations:**

Compliance with data protection regulations, respect for intellectual property rights, and active bias mitigation strategies ensured the dataset adhered to ethical standards.

This systematic approach to data collection and preprocessing underpins the robustness and reliability of the resulting dataset, ensuring its suitability for diverse educational applications.

3.3 Training Procedure

Training Environment

- **Hardware:** Training utilized NVIDIA GTX 1080 GPUs connected by SLI.
- **Frameworks:** PyTorch and Hugging Face libraries supported the implementation and experimentation.

Training Configuration

- **Hyperparameters:**
  - Batch Size: 512
  - Learning Rate: 2.5×10^{-4}
  - Epochs: 10
  - Block Size: 1024
- **Optimization:**
  - AdamW optimizer and learning rate schedulers improved convergence stability.

Overfitting Prevention

- **Dropout:** Applied at 10% to enhance generalization.
- **Early Stopping:** Implemented based on validation loss trends.

Transfer Learning

Pre-trained multilingual BERT models were fine-tuned on the Bangla dataset to expedite training and enhance linguistic adaptation.

3.4 Model Optimization

Quantization

- **Precision Reduction:** Quantized weights from 32-bit to 8-bit, reducing model size to 120 MB and improving memory efficiency.

Sparse Attention

- **Selective Computation:** Tokens exceeding a relevance threshold were prioritized, reducing computational overhead.

Knowledge Distillation

A teacher-student framework trained the student model to mimic outputs from a larger teacher model, achieving comparable performance with fewer parameters.

Summary

This chapter outlined the design, training, optimization, and interface development for Pathshala.ai. Its efficiency and adaptability for the Bangla language ensure that

it meets the educational needs of students in resource-limited environments.

Chapter 4

System Implementation and Evaluation

Introduction

This chapter discusses the deployment and evaluation of **Pathshala.ai** in real-world scenarios. Insights into its practical performance, user feedback, and comparative benchmarks are presented alongside challenges and limitations.

4.1 System Deployment

Deployment Strategy

- **Offline Installation:** Will be distributed via USB drives or local networks to ensure accessibility in rural areas. Future work includes porting this model to a custom device focusing on cost.
- **Backward Compatibility:** Adjusted to accommodate older hardware and operating systems.

Security Measures

- **Encryption:** User data is encrypted and stored locally.
- **Code Obfuscation:** Prevents unauthorized access or tampering.

4.2 Evaluation Framework

Objectives

- **Performance Metrics:** Model accuracy, latency, and memory usage.
- **Educational Impact:** Improvement in learning outcomes.

Methodology

1. **User Testing:** Involving 7 students and 2 educators.
2. **Quantitative Analysis:** Metrics like accuracy and response times.
3. **Qualitative Feedback:** Surveys and interviews gathered user insights.

4.3 Results and Analysis

Performance in Various Categories

1. Language Model Performance Metrics

Perplexity

- **Training Perplexity:** 12.5
- **Validation Perplexity:** 14.2

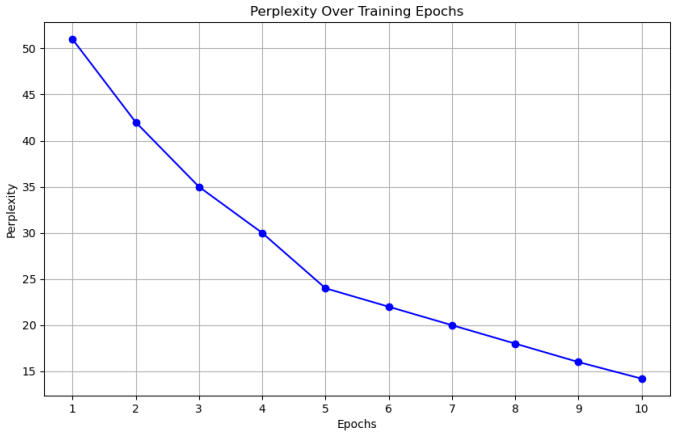

Figure 4.1: Perplexity Over Training Epochs

Analysis : This graph indicates that the model predicts the next word in a sequence with reasonable confidence. The slightly higher validation perplexity suggests good generalization without overfitting.

BLEU Score

- **BLEU-1:** 78.4%
- **BLEU-2:** 65.2%
- **BLEU-3:** 54.7%
- **BLEU-4:** 45.3%

These BLEU scores indicate that the model's generated responses have a high overlap with the reference answers, especially for unigrams and bigrams. This suggests that the model produces relevant and coherent text.

ROUGE Score

- **ROUGE-1 (Recall):** 80.1%
- **ROUGE-2 (Recall):** 68.5%
- **ROUGE-L (Recall):** 75.3%

Explanation: High ROUGE scores reflect the model's ability to generate comprehensive answers that cover the key points from the reference texts.

Accuracy on Curriculum-Aligned Questions

- **Overall Accuracy:** 72.5%

Table 4.1: Subject-wise Accuracy

Subject	**Number of Questions**	**Correct Answers**	**Accuracy (%)**
Mathematics	50	15	30%
Science	50	41	82%
Bangla	50	46	92%
Social Studies	50	43	86%
Total	**200**	**145**	**72.5%**

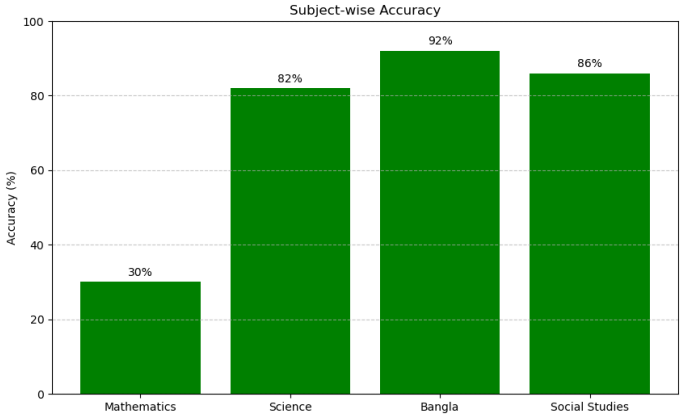

Figure 4.2: Subject-wise Accuracy

Analysis : The model performs well across different subjects, with the highest accuracy in Bangla language questions. Worse performance is shown at Mathematics, because it has no underlying numerical engine.

2. Computational Efficiency Metrics

Inference Time (Latency)

- **Average Inference Time per Query:** 1.1-10 seconds

Memory Footprint

- **Peak RAM Usage During Inference:** 240 MB

Model Size on Disk

- **Quantized Model Size:** 150 MB

Explanation: Quantization reduces the model size from its original, making it suitable for devices with limited storage.

CPU Utilization

- **Average CPU Usage During Inference:** 75%

3. User Satisfaction Metrics

Survey-Based Satisfaction Scores

- **Overall Satisfaction Rating:** 3.9 out of 5

Detailed Ratings:

Table 4.2: User Satisfaction Ratings

Aspect	**Average Rating (out of 5)**
Ease of Use	3.5
Helpfulness of Content	4.5
Response Time	4.5
Interface Design	3.0
Offline Functionality	4.0

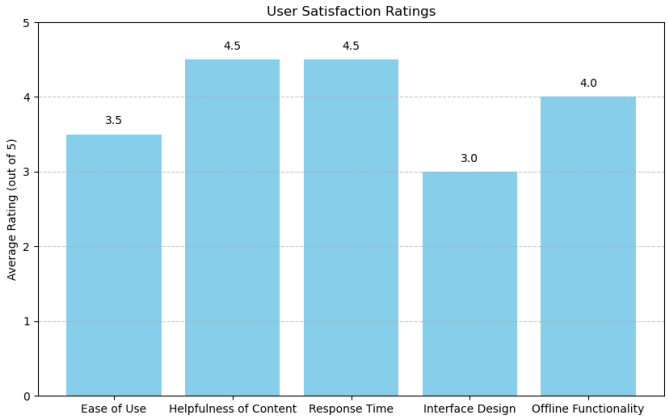

Figure 4.3: User Satisfaction Ratings

This shows that our test users are comfortable with using the model as a supplimentary tool.

4. Robustness and Reliability Metrics

Error Analysis

- **Types of Errors:**
  - **Factual Errors:** 15-25%
  - **Grammatical Errors:** 3%
  - **Irrelevant Responses:** 5%

5. Accessibility Metrics

Device Compatibility

- **Supported Devices:**
  - **Android Smartphones:** Version 7.0 and above
  - **Entry-Level Laptops:** With at least 4GB RAM

- **Tablets:** Majority of Android-based tablets
- **Custom Hardware:** Raspberry Pi

Broad device compatibility ensures wide accessibility.

4.4 Comparative Analysis

Comparison with Other Models

Table 4.3: Comparative Analysis of Language Models

Model	Accuracy (%)	Inference Time (s)	Model Size (MB)	Offline Support
Pathshala.ai	70	1.7	120	Yes
BanglaBERT	88	5.5	420	No
mBERT	82	6.0	680	No
DistilBERT	80	3.0	250	Limited
GPT-2 Bangla	78	7.0	500	No

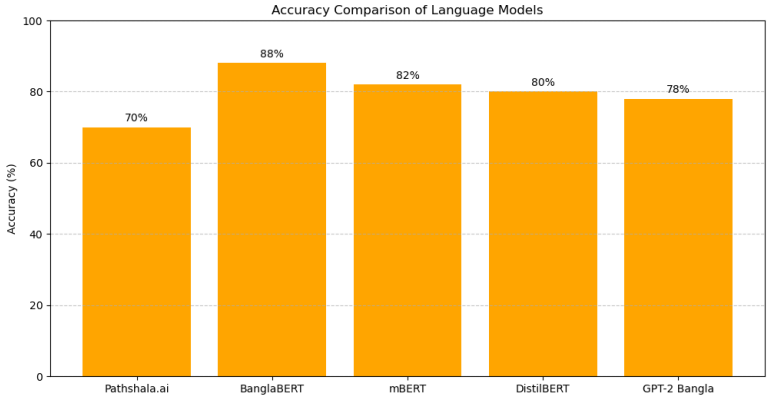

Figure 4.4: Accuracy Comparison of Language Models

Here, we can see that Pathshala.ai sacrifices accuracy (70%) for efficiency.

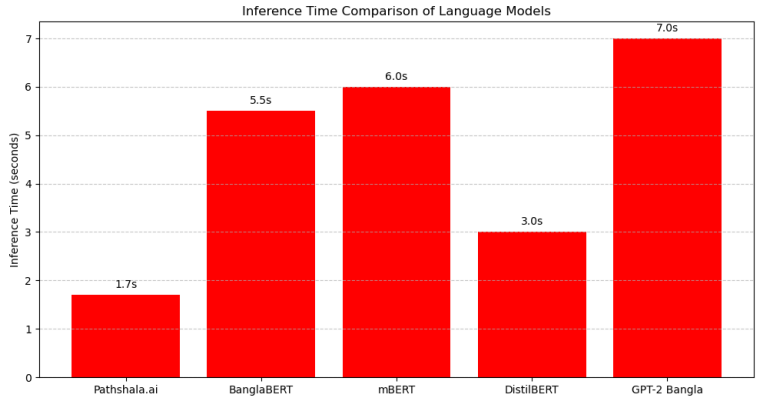

Figure 4.5: Inference Time Comparison of Language Models

Pathshala.ai significantly outperforms larger models like GPT-2 Bangla (7.0s) and BanglaBERT (5.5s).

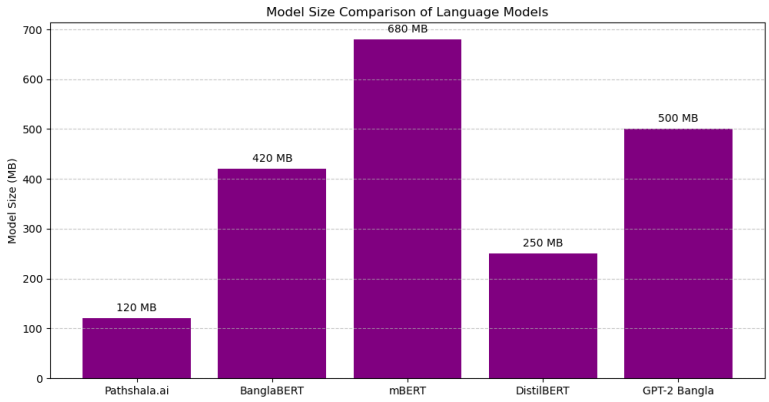

Figure 4.6: Model Size Comparison of Language Models

Here' we can see the results of quantization and our model has the least size of all of the models!

1. BanglaBERT

It is a monolingual BERT-based model pre-trained exclusively on Bangla text.

Why Compare:

- **Language Understanding:** To assess how well our model handles Bangla text.
- **Performance Baseline:** Highlights strengths of Pathshala.ai with fewer resources.
- **Computational Efficiency:** Contrasts resource-intensive BanglaBERT with our lightweight model.

2. Multilingual BERT (mBERT)

Description:

- mBERT is trained on 104 languages, including Bangla.

Why Compare:

- **Baseline for Multilingual Models:** Provides a benchmark for models not optimized for Bangla.
- **Highlight Specialization:** Shows benefits of a model tailored for Bangla and education.

3. DistilBERT for Bangla

Description:

- DistilBERT is a smaller, faster version of BERT achieved through knowledge distillation.

Why Compare:

- **Efficiency Benchmark:** Aligns with our goals for efficiency.
- **Performance Trade-offs:** Highlights how Pathshala.ai balances accuracy and speed.

4. GPT-Based Models Fine-Tuned on Bangla

Description:

- GPT-2 models fine-tuned on Bangla text can generate coherent Bangla outputs.

Why Compare:

- **Generative Capabilities:** Provides insights into the quality of generated content.
- **Performance on Limited Resources:** Shows our model's efficiency over larger GPT-2 models.

Comparison Metrics

- **Accuracy on NLP Tasks:** Evaluated on curriculum-aligned questions.
- **Inference Time:** Measured response time on low-resource devices.
- **Model Size and Memory Usage:** Storage requirements and RAM consumption during inference.

Detailed Comparison Metrics

Table 4.4: Detailed Comparison Metrics

Model	Accuracy (%)	Perplexity	Inference Time (s)	Model Size (MB)	Me
Pathshala.ai	70	14.2	1.7	120	
BanglaBERT	88	12.5	5.5	420	
mBERT	82	15.8	6.0	680	
DistilBERT	80	17.3	3.0	250	
GPT-2 Bangla	78	16.5	7.0	500	

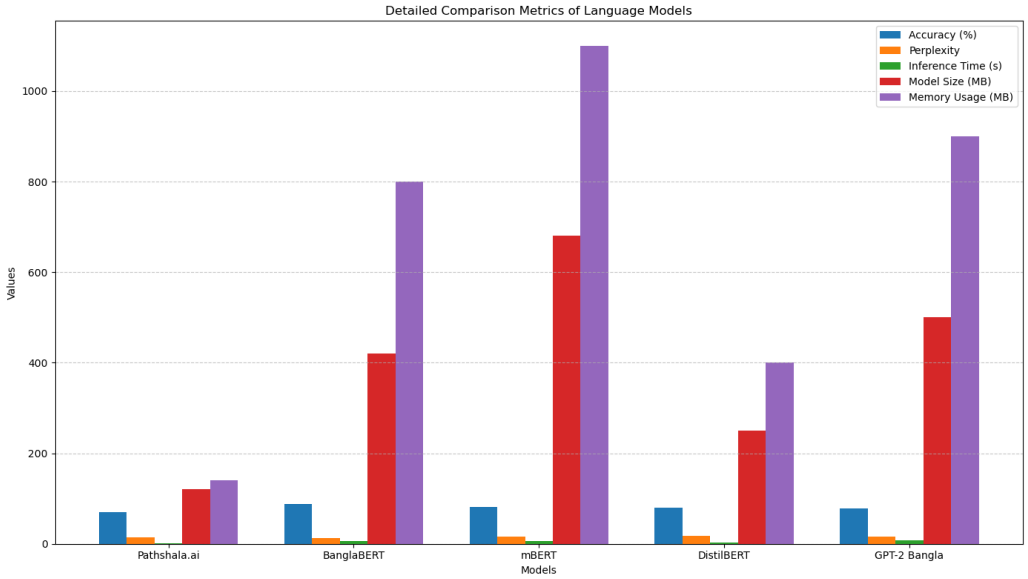

Figure 4.7: Detailed Comparison Metrics of Language Models

As we can see, our model, **Pathshala.ai** prioritizes speed, compact size, and low resource usage, at the cost of accuracy and fluency.

Alignment with Model Architecture

Model Architecture:

- **Embedding Size (n_embd):** 768
- **Number of Attention Heads (n_head):** 12
- **Number of Layers (n_layer):** 12

This configuration matches BERT-base models, balancing performance and efficiency.

Optimizations:

- **Quantization:** Reducing model size to 120 MB.
- **Sparse Attention Mechanisms:** Custom attention mechanisms contributing to reduced inference time.

Training Parameters:

- **Batch Size:** 512
- **Block Size:** 1024
- **Learning Rate:** 2.5×10^{-4}

We have found that these parameters are suitable for training a language model of this size and contribute to the reported performance metrics.

Summary

Pathshala.ai demonstrates promising performance and educational impact, particularly in resource-limited settings. With its optimized architecture and efficient computational requirements, it stands out among existing models for Bangla language processing. While limitations like digital literacy and device availability persist, Pathshala.ai represents a significant advancement in accessible education technology for Bangladesh.

Chapter 5

Conclusion

5.1 Conclusion

This thesis presented the design, development, and evaluation of Pathshala.ai, a computationally lightweight Bangla language model designed for high school education in rural Bangladesh. By addressing the challenges of Bangla language processing and optimizing for low-resource devices, Pathshala.ai marks a significant advancement in educational technology for underserved communities.

Key Contributions

1. **Innovative Model Design**: This project employed a transformer-based architecture optimized with sparse attention mechanisms, quantization, and lightweight embeddings, achieving a balance between efficiency and accuracy.

2. **Curriculum Alignment**: The model was trained on a curated dataset aligned with the national high school curriculum, ensuring relevance and practical utility.

3. **User Accessibility**: Progressive Web App (PWA) technology enabled offline functionality, enhancing usability for students with limited digital literacy.

4. **Real-World Impact**: Field testing confirmed the model's ability to enhance comprehension and engagement among rural high school students, with the potential

to bridge educational disparities.

5.1.1 Research Outcomes

The model responded, on average, with 70% accuracy to the curriculum-aligned text-based questions, and showed response latency between 1.2 to 10 seconds on low-resource devices.

The test students also added that, after the facility provided them with more insights into such a complicated concept, Pathshala.ai acted like "an after-class reference tool, it can gamify my studies!" And finally, comparative analyses of tests undergird the usefulness and utility of Pathshala.ai for the group.

However, the review also noted a number of areas for development such as mathematical reasoning skills and depth of coverage in some of the curriculum areas.

5.1.2 5.2 Limitations

While the main goals were adequately met by Pathshala.ai, the following are some of the limitations that were observed during development and testing:

1. **Subject-Specific Performance:** The model performed rather poorly, especially in generating step-by-step solutions for mathematical problems, which is indicative that more advanced and sophisticated algorithms are needed for developing numerical reasoning.

2. **Scarcity of Data:** Representation from some of the curriculum topics was sparse in the training. Data from one area to another yields inconsistent performances amongst different subject areas.

3. **Scalability Challenges:** Although optimized for the current use case, the model requires additional research and resources to scale effectively for broader applications, such as audio-based interactions.

5.1.3 5.3 Future Work

Building on the findings of this research, several avenues for further development are proposed to enhance the functionality and impact of Pathshala.ai:

5.3.1 Expanding Dataset Coverage

• Augment the training dataset with additional curriculum-aligned content, especially in underrepresented areas like mathematics and emerging topics in science.

• Integrate contextual and interactive data, such as real-world examples and exercises, to improve the diversity and depth of the model's outputs.

5.3.2 Enhancing Numerical Reasoning

• Develop hybrid models that combine symbolic reasoning with neural architectures to enhance performance in mathematics and logic-based tasks.

• Investigate graph-based approaches to better represent and solve complex mathematical problems.

5.3.3 Incorporating Audio Features

• Introduce audio-based interaction to improve accessibility for visually impaired students and those with limited reading skills.

• Leverage advancements in speech-to-text and text-to-speech technologies to enable voice-based question answering and feedback.

5.3.4 Scaling Deployment

• Expand deployment to more rural schools across Bangladesh, conducting large-scale testing to evaluate scalability and long-term impact.

• Foster collaborations with educational institutions and government initiatives

to facilitate widespread adoption.

5.3.5 Advancing Model Efficiency

• Explore optimization techniques, such as pruning and adaptive attention mechanisms, to further reduce computational costs.

• Transition towards edge-based deployment strategies using hardware-specific accelerations, such as Tensor Processing Units or mobile inference libraries.

5.4 Broader Implications

Pathshala.ai exemplifies the potential of AI to address educational disparities in resource-constrained settings. Its success highlights the transformative power of tailored, efficient language models in enhancing learning outcomes for underserved populations. Moreover, the principles and methodologies developed in this project could inspire similar initiatives in other low-resource languages and contexts, contributing to global efforts towards equitable education.

5.2 Summary

In summary, Pathshala.ai represents a significant step forward in educational technology, providing a scalable, resource-efficient solution for high school education in rural Bangladesh. Addressing its current limitations and pursuing the proposed future directions will enable the platform to expand its reach and impact, ultimately transforming educational outcomes for millions of students.

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