3D Magnetic Resonance Image Super-Resolution Reconstruction

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Client: Xia Li

Mentor`s name: Xia Li

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Catalogue

Abstract

The graduation project topic for our group is the design of an image super-resolution reconstruction algorithm. The goal is to accurately restore blurred details and microstructures from low-resolution images, thereby obtaining high-resolution clear images rich in information. In simple terms, it involves using a super-resolution algorithm to transform originally blurry images into clear ones.

This algorithm only processes images and does not involve other aspects of the image capture process. While the algorithm can be applied to most fields, our group is currently focusing solely on the medical field, specifically targeting the restoration of magnetic resonance imaging (MRI) images.

Our group plans to complete the project proposal by October 22, 2025, and finish building the algorithm within eight months. We will construct a deep learning network to achieve super-resolution reconstruction of magnetic resonance images.

The complete algorithm development process begins with data processing: selecting a portion of a 3D brain MRI dataset, dividing it into small square regions based on different areas, and splitting it into training, validation, and test sets in a 7:2:1 ratio. The training set will be formed by downsampling the images. Next, we will conduct comparative experiments. First, we will reconstruct images using existing algorithms from the literature and compare them with the test set. Then, based on these existing algorithms, we will create

our own reconstruction algorithm, generate reconstructed images, and compare them with the test set to complete the comparative experiments. Following this, we will perform ablation experiments to optimize the algorithm itself. We will refine our self-built algorithm by adding certain steps and removing unnecessary ones to enhance image clarity.

Finally, we will process the results by performing a pixel-wise difference comparison between the reconstructed images and the high-resolution images, thereby completing the entire algorithm development.

The risk associated with this algorithm is insufficient reconstruction accuracy and the presence of pseudo-details, meaning the images may appear visually clear, but the pathological features of lesions might deviate from those in the real high-resolution images.The difficulty of this algorithm lies in the reconstruction of 3D images. It requires dividing the target model into block regions of uniform size, which is quite challenging since it is not a 2D planar graph.

The estimated cost for this project is within 1,000 RMB.

Terms Of Reference

2.1 Project Background

2.1.1 Project Introduction

Image super-resolution reconstruction is a classical low-level vision problem in the field of computer vision. Its objective is to accurately restore blurred details and microstructures from low-resolution images, thereby obtaining high-resolution clear images rich in information. Magnetic resonance imaging (MRI) has become an essential auxiliary tool in medical diagnosis and treatment processes. However, limited by physical equipment, low-resolution magnetic resonance images often suffer from severe motion artifacts, limited scan spatial coverage, and poor image quality. These issues can lead to the loss of critical information and unclear visualization of lesions.

2.1.2 Objectives

In the task of image super-resolution reconstruction, processed images are treated as the real high-resolution images, and corresponding low-resolution images are obtained through downsampling. Deep learning-based super-resolution methods are employed to reconstruct low-resolution images at different magnification factors. To objectively evaluate the experimental results of different methods, this proposal adopts two commonly used evaluation metrics—Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM)—to assess the reconstruction results of various approaches. Higher values of PSNR or SSIM indicate better reconstruction outcomes.

2.2 Client Organization Details

The client contact is Li Xia, who also serves as the advisor for the "3D MRI Super-Resolution Reconstruction" project. Her email address is lixia.cjlu.edu.cn. The project she is promoting falls under the category of "Data Processing + Programming" and focuses on the research and development of super-resolution reconstruction technology in the field of magnetic resonance imaging. The team is required to possess skills such as Python programming and medical image data processing. The project duration is two semesters (from September to May of the following year), with the goal of enhancing the quality of magnetic resonance images by constructing a deep learning algorithm framework, thereby providing technical support for medical diagnosis.

Rationale For The Project

3.1 Project Necessity

This approach can mitigate the hardware limitations of magnetic resonance imaging. Due to constraints in equipment performance, low-resolution MR images are prevalent, which can directly lead to the loss of critical medical information and unclear visualization of lesions, thereby affecting doctors' accurate diagnosis. However, by employing image super-resolution (SR) reconstruction technology, the quality of MR images can be effectively enhanced, making it a necessary low-cost yet effective solution to address the aforementioned challenges.

3.2 Existing Systems

The project has investigated current mainstream 3D medical image super-resolution reconstruction methods, covering solutions based on different technical approaches such as Generative Adversarial Networks (GANs), Transformers, and DenseNet. Specific examples include:

Volumetric super-resolution technology based on 3D RRDB-GAN, which can be used for 3D detail restoration in radiological images;

Multi-scale feature extraction and reconstruction methods optimized for inter-slice correlation features in 3D MRI images;

A 3D medical image super-resolution solution based on DenseNet, which enhances reconstruction effectiveness through feature reuse.

3.3 Core Issues and Opportunities

3.3.1 Core Issues

The core issue of the project lies in how to accurately restore critical details such as lesion textures and edges in low-resolution magnetic resonance images through deep learning networks, while avoiding the generation of pseudo-details or the loss of authentic details. It also addresses the alignment between technical metrics (PSNR, SSIM) and clinical efficacy, while tackling the insufficient generalization capability of models on diverse and complex low-resolution magnetic resonance data (e.g., from different scanning devices, parameters, and artifact levels). Additionally, there is the challenge of unbalanced reconstruction accuracy of a single model at different magnification factors such as 2× and 4×.

3.3.2 Project Opportunities

The project opportunity is reflected in the fact that a successfully constructed 3D magnetic resonance image super-resolution model can be directly applied in clinical settings to assist doctors in improving diagnostic accuracy. If breakthroughs are achieved in reconstruction accuracy or model efficiency, it can form a competitive technical solution and provide references for related research. Moreover, the technology's characteristics of low cost and ease of deployment make it adaptable to existing equipment in various medical institutions, offering primary healthcare institutions a low-cost solution to enhance magnetic resonance image quality, thereby possessing both clinical value and market potential.

Objective And Scope

4.1 Project Objectives

4.1.1 Core Objective

To construct a deep learning-based 3D magnetic resonance (MR) image super-resolution reconstruction model capable of precisely reconstructing low-resolution (LR) brain MR images into high-resolution images, and subsequently validate whether the reconstruction accuracy of this algorithmic model meets the target.

4.1.2 Deliverables

A functional 3D MR image super-resolution deep learning model (based on the PyTorch framework)（Wu, Q. (2023). An arbitrary scale super-resolution approach for 3D MR images via implicit neural representation. IEEE Journal of Biomedical and Health Informatics. https://doi.org/[Insert Paper DOI]）. Preprocessed low-resolution datasets, the reconstructed datasets, and the original high-resolution datasets. Comparative experiment reports, ablation study reports, project technical report, and a final summary report.

4.2 Project Scope

4.2.1 Functional Requirements

Requirement Category	High-Level Requirement Description
Data Processing	1. Support preprocessing operations for brain MR images, such as

Requirement Category	High-Level Requirement Description
Requirements	format conversion, noise removal, and normalization. 2. Support automatic division of the dataset into training, validation, and test sets in a 7:2:1 ratio, and ensure the data format meets the input requirements for model training.
Model Construction and Training Requirements	1. Construct a 3D deep learning network architecture that supports the integration of different functional modules (e.g., feature extraction modules, feature fusion modules). 2. Support comparative experiments to refine the algorithm by comparing different reconstruction methods. 3. Support ablation experiments, i.e., by enabling/disabling specific modules in the network, compare the reconstruction metrics of different module combinations at 2× and 4× magnification factors.
Model Testing and Comparison Requirements	1. Support performance evaluation of the trained model using the test set, automatically outputting PSNR and SSIM values along with the reconstructed HR images. 2. Support comparison of the proposed model with other representative super-resolution methods (e.g., 3D RRDB-GAN, lightweight 3D Transformer), and output multi-method metric comparison tables and visual comparison charts of image results.

Lightweight 3D Super-Resolution Reconstruction Network

Its basic structure is shown in Figure 1, which mainly consists of three parts:

shallow feature extraction, deep feature extraction, and upsampling reconstruction. Among them, ILR refers to the small cube images cropped from degraded 3D images, and ISR represents the corresponding reconstructed images.

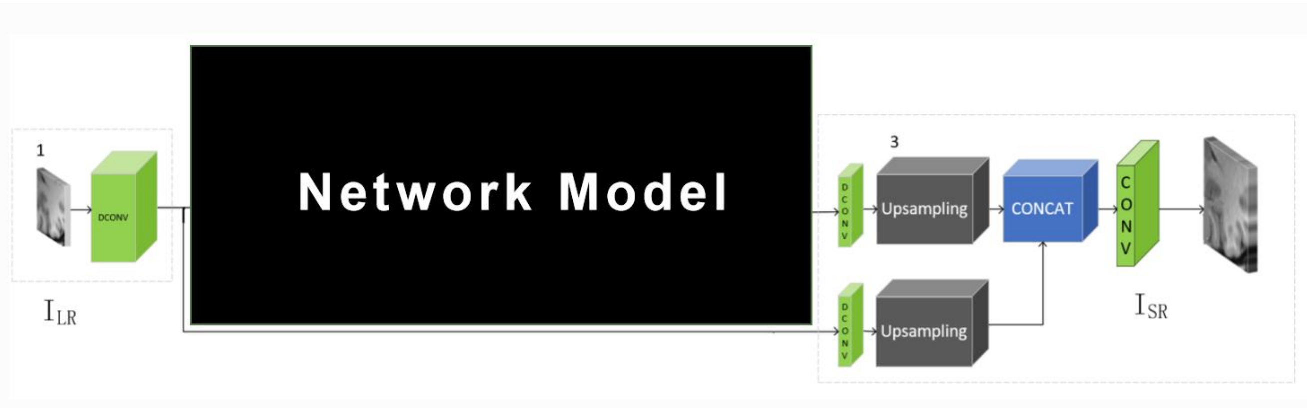


Figure 1: Structure Diagram of the Lightweight 3D Super-Resolution Reconstruction Network

First, the ILR is input into the shallow feature extraction module, where a dilated 3D convolutional layer is used to extract shallow features. Then, the shallow features are fed into the deep feature extraction module. This module is composed of N stacked Reverse Residual Attention Fusion (RRAF) blocks—with N determined through ablation experiments—and a feed-forward transformer module is added at the end to capture more useful contextual information. The feed-forward transformer consists of two components: the multi-Depthwise Dilated Convolution (DDConv) head transposed attention (MDDTA) and the gated-DDConv feed-forward network (GDDFN). Finally, the shallow features and the output from the deep feature extraction module are each subjected to upsampling operations, and the final output ISR is obtained after concatenation and convolution.

4.2.2 Non-Functional Requirements

Requirement Category	High-Level Requirement Description
Performance Requirements	The model's reconstruction time for a single brain MR image should not exceed 5 minutes at 2× and 4× magnification factors (on a standard configured computer).
Compatibility Requirements	The model code must be compatible with both Windows and Linux operating systems.
Maintainability Requirements	1. The code must contain clear comments and be accompanied by detailed usage documentation to enable team members or subsequent users to quickly understand and modify it. 2. Experimental data (including raw data, training logs, and metric results) must be categorized and stored according to established specifications to facilitate tracking and reuse.

4.3 Technical Infrastructure and Skills for High-Level Requirement Implementation

4.3.1 Infrastructure Requirements

Infrastructure Category	Specific Requirements
Hardware Facilities	1. Computer: Must be equipped with a GPU (VRAM ≥ 12GB, e.g., NVIDIA RTX 3090 or higher), CPU ≥ 8 cores, RAM ≥ 32GB, and hard drive storage space ≥ 1TB (for storing datasets and training logs). 2. Network Environment: A stable internet connection is required for downloading open-source datasets, the PyTorch framework, and related dependency libraries.
Software Facilities	1. Operating System: Windows 10 or above, or Linux (e.g., Ubuntu 18.04 or above). 2. Development Frameworks & Tools: PyTorch 1.8 or above, Python 3.7-3.9, OpenCV (for image preprocessing), SimpleITK (for reading and processing medical images), Matplotlib (for visualizing experimental results), Git (for code version control).

4.3.2 Technical Requirements

Proficiency in the Python programming language and skilled in dataset processing (including data downsampling, classification, etc.). Understanding of super-resolution reconstruction principles and familiarity with existing reconstruction methods documented in the literature. Capable of independently designing comparative and ablation experiments and writing reports.

4.3.3 Infrastructure Provided by AUT or the Client

Dataset Support: Provision of the Kirby21 brain dataset.

Hardware Support: Provision of computers with high-performance GPUs for model training and large-scale data processing.

Software and Permission Support: Provision of installation guidance for the PyTorch framework and related dependency libraries, or provision of virtual machines/containers with pre-configured development environments.

Technical Consultation Support: Assistance provided to team members when they encounter difficulties.

Skills Analysis

5.1 Skills Required for the Project

5.1.1 IT Professional Skills

Skill Category	Specific Skills and Knowledge Requirements
1. Programming Languages & Tool Application	Proficient in Python programming, with a solid grasp of data structures and file I/O operations. Capable of utilizing Python third-party libraries for image reading, format conversion, noise reduction, and other preprocessing tasks.
2. Deep Learning Framework & Model Development	Mastery of core PyTorch operations, including tensor computations and model training.
3. Data Processing & Analysis	Proficient in techniques such as image downsampling, normalization, and data augmentation.
4. Super-Resolution Algorithm Theory & Practice	Understanding of the fundamental principles of image super-resolution (SR) and familiarity with the logic of 3D super-resolution network architectures. Mastery of PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity) metric calculation methods, enabling the evaluation of reconstruction effectiveness based on these metrics.

5.1.2 Personal Professional Skills

Competency Category	Specific Requirements
1. Foundational Knowledge in Medical Imaging	Understand the basic principles of Magnetic Resonance Imaging (MRI); be aware of common issues in low-resolution (LR) MR images; able to distinguish between "clinically critical details" (such as lesion boundaries and textures) and irrelevant noise.
2. Experimental Design and Problem Troubleshooting	Possess clear experimental logic; able to design ablation experiments using the "controlled variable method" (e.g., with the single variable being "whether to add a specific network module"); capable of identifying common issues during model training and resolving encountered problems.
3. Team Collaboration and Communication	Able to establish clear division of labor within a 4-person team and synchronize progress; capable of clearly communicating technical challenges to the project advisor and obtaining guidance.

Competency Category	Specific Requirements
4. Documentation and Results Consolidation	Able to write technical documents and experimental reports according to standards; capable of compiling the entire project process into a comprehensive final project summary report.

5.2 Analysis of Team Knowledge Gaps

Gap Category	Specific Gap Description
1. IT Professional Skill Gaps	- Insufficient experience in 3D deep learning network development: Unfamiliar with super-resolution for 3D images and lack practical experience in handling spatial features. - Weak application of specialized medical imaging tools: Unfamiliar with medical image processing libraries, leading to low efficiency in MR image format conversion and preliminary artifact processing. - Unfamiliarity with Python: The team's academic curriculum has only covered C and Java, resulting in a lack of knowledge regarding Python.
2. Comprehensive Competency Gaps	- Lack of foundational knowledge in the medical imaging field: The team has limited understanding of the clinical definitions of "lesion characteristics" in MR images, making it difficult to specifically validate the "reconstruction effectiveness of lesion details" during experimental design. - Insufficient capability for troubleshooting complex experimental issues: When facing problems such as "significant discrepancies in metrics across different magnification factors" or "poor comparative performance of the model against other SR methods," the team may struggle to quickly identify the root causes (e.g., data distribution bias, redundant network modules).

5.3 Skill Acquisition Timeline

The project cycle runs from October to May of the following year. Skill acquisition will be phased as "early-stage learning → mid-term practice → late-stage optimization," with sufficient time allocated for development:

October - November (Early-stage Learning): Through self-study of online courses, reviewing project-related literature, and consulting with the advisor to supplement knowledge of medical imaging, complete a 3D network building demo and a summary of relevant literature.

December - March of the following year (Mid-term Practice): Adopt a "learning-by-doing" approach to strengthen skills in dataset processing techniques and enhance technical abilities during model training. Concurrently, hold weekly team seminars for mutual assistance and peer learning. Upon completing each set of ablation experiments, utilize the GitHub community to troubleshoot issues. Complete dataset preprocessing and the construction of the 3D super-resolution model.

April - May of the following year (Late-stage Optimization): Focus on learning performance optimization techniques to address issues like poor comparative model performance. Simultaneously, learn technical documentation standards by referring to templates provided by the advisor. Complete all comparative experiments and the writing of the final documentation.

Team Roles

Zhang Zhexuan:

Responsibilities: Team Leader : Responsible for overall coordination and task planning for other team members.

Data Processing:Handles dataset preprocessing, downsampling, and categorization.

Algorithm Model Development :Assists in building parts of the super-resolution reconstruction algorithm model.

Dong Eryihan:

Responsibilities: Algorithm Model Development – Primarily responsible for constructing the super-resolution algorithm model.

Ablation Experiments – Conducts ablation experiments to optimize the performance of the algorithm model.

Song Xinchi:

Responsibilities:Comparative Experiments – Performs comparative experiments to evaluate the reconstruction accuracy of images generated by different super-resolution algorithms against the original images and identifies the optimal algorithm construction method.

Documentation : Assists in partially drafting the final summary report.

Shi Yujie:

Responsibilities: Testing – Responsible for testing bugs in the developed algorithm models and improving their performance.

Documentation : Primarily responsible for drafting the final summary report.

Team Schedule For Part1

7.1 Off-Site Work Phase Schedule (Proposal Phase, 12-15 hours per week)

Project Phase	Core Tasks	Responsible Person	General Duration
Early Project Stage	MRI dataset preprocessing (format conversion, noise reduction, downsampling)	Zhexuan Zhang	Lasting 2-3 phases
Mid-Project Stage	3D model construction & code debugging; comparative experiment design	Eryihan Dong, Xinchi Song	Lasting 3-4 phases
Full Project Cycle	Weekly team progress sync meetings; model testing & bug fixing	All Team Members	Conducted regularly in each phase
Mid-Late Project Stage	Experimental data organization; draft document writing	Yujie Shi	Lasting 2-3 phases

7.2 Mentor & Client Meeting Schedule

Meeting Participant	Frequency	Core Topics	Minutes Recorder
Mentor (Xia Li)	**Once per week**	**Progress update, technical difficulty consultation, experimental plan adjustment suggestions**	**Zhexuan Zhang**
Client (Xia Li)	**Once every 2 weeks**	**Dataset requirement confirmation, clinical demand alignment**	**Yujie Shi**

Project Management Methodology or Approach

8.1 Selected Methodology: Agile Development (Scrum Framework)

Rationale: This project focuses on deep learning algorithm development, requiring frequent iterative verification. The "short-cycle sprint + rapid feedback" model of Scrum is suitable for such needs. The team has clear division of labor, which can ensure collaboration through simplified role alignment. The client (mentor) needs to continuously participate in demand confirmation, which is consistent with Scrum's feedback mechanism.

8.2 Work Breakdown Structure (WBS)

Project Phase	Core Activities	Deliverables	General Cycle
Initiation Stage	Client demand interview, project goal decomposition	Demand specification document, project goal list	1-2 weeks in the early project stage
Planning Stage	Formulation of skill gap filling plan, experimental plan design, risk register establishment	Skill learning schedule, experimental design document, risk list	2-3 weeks in the early project stage
Execution Stage	Data processing, 3D model development, comparative/ablation experiments	Preprocessed dataset, operable basic model, original experimental data	4-6 weeks in the mid-project stage
Monitoring Stage	Weekly risk review, phased result review	Risk tracking report, phased review document	Full project cycle
Closure Stage	Result integration, document archiving, project review	Final technical report, complete project archive	2-3 weeks in the late project stage

Risk And Issues Management

9.1 Risk Identification & Mitigation Measures

Risk Category	Specific Risk Description	Impact Level (1-5)	Probability (1-5)	Mitigation Measures
Technical Risks	Failure to build 3D network, inability to extract spatial features of MRI images	5	3	First build a 2D network to verify logic, then expand to 3D; refer to open-source projects; consult the mentor
Resource Risks	Insufficient GPU memory, interrupting model training	4	2	Prioritize using equipment provided by the client; adopt model lightweight strategies;
Schedule Risks	Ablation experiments taking longer than expected, delaying model optimization	3	4	Plan experiments by priority; conduct some tests in parallel; reserve 2 weeks of buffer time
Quality Risks	False details in reconstructed images, deviation of clinical features	5	3	Add clinical feature constraints; invite the mentor to participate in result evaluation; increase the proportion of real clinical data testing

9.2 Monitoring and Control Process

Risk Monitoring: Sync the "Risk Register" in weekly team meetings to update risk status; report progress on high-impact risks (impact ≥4) to the mentor every 2 weeks.

Issue Handling: Submit an "Issue Report" within 12 hours of identifying a problem; hold a review meeting within 24 hours to develop solutions; verify the effect within 48 hours after resolution.

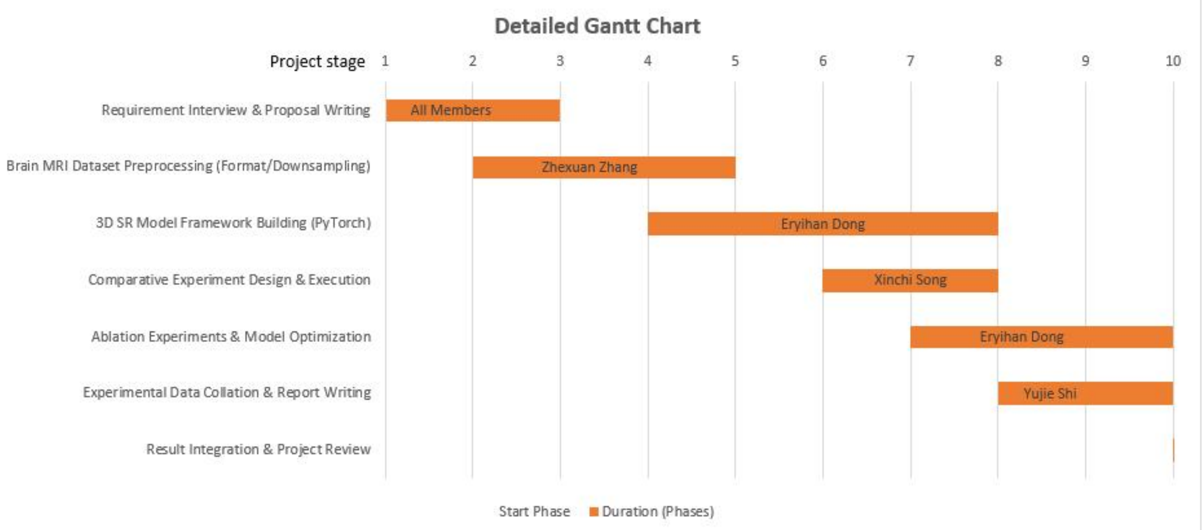
Emergency Mechanism: Activate alternative plans when core resources are interrupted, and simultaneously apply for support from the client to ensure schedule delays do not exceed 3 days (specific plan to be determined).

Project Plan

10.1 High-Level Schedule (Proposal Phase)

Project Phase	**Key Tasks**	**Milestones**	**General Timeline**	**Associated AUT Assessment Tasks**
Initiation Stage	Demand interview, goal decomposition	Proposal defense completion	Early project stage	Proposal report (10.23)
Planning Stage	Skill learning, experimental plan design	Experimental plan confirmation	Early project stage	to be determined
Execution Stage	Data processing, model development, experimental verification	Operable basic model, experimental data archiving	Mid-project stage	Mid-project review (to be determined)
Monitoring Stage	Result review, model optimization	Delivery of optimized model	Mid-late project stage	to be determined
Closure Stage	Document integration, result submission	Delivery of final report	Late project stage	Final reflective report (to be determined)

10.2 Detailed Gantt Chart (Including Timeline and Resource Allocation)



Estimate All Costs Incurred

11.1 Resource Costs (RMB)

Cost Category	**Specific Items**	**Estimated Amount**	**Calculation Basis**
Data-Related	Dataset storage (hard disk), emergency annotation tools	RMB 500	Approximately RMB 400 for a 1TB mobile hard disk; RMB 100 reserved for emergencies
Software-Related	Cloud GPU rental	RMB 300	RMB 100 per month (for about 3 months); prioritize using client-provided equipment
Others	Document printing, collaboration tool membership	RMB 200	RMB 50 for printing; RMB 150 for tool membership (for about 6 months)
Subtotal	-	**RMB 1,000**	Consistent with the initial budget

11.2 Mentor Hourly Cost (NZD, including GST)

Hour Calculation: 1 meeting hour per week, total project cycle approximately 36 weeks (to be determined), total hours about 36.

Total Cost: 142 × 36 = NZD 5,112

11.3 Total Budget Explanation

11.3.1 Budget Composition

The total project budget consists of two parts: resource costs and advisor labor costs. The specific details are as follows:

Resource Costs: 1,000 RMB. This primarily covers basic resource expenditures such as dataset storage equipment, backup cloud GPU rental, document printing, and team collaboration tool memberships. This portion of the cost has been strictly controlled within the initial budget range.

Advisor Labor Costs: 8,378 NZD. This is calculated based on the academic supervision hourly rate stipulated by the university, covering core advisory activities including regular guidance, meeting participation, milestone reviews, and specialized technical consultations.

11.3.2 Currency Conversion Note

As resource costs are accounted for in RMB while advisor labor costs are in NZD, currency conversion based on the current exchange rate (subject to the actual settlement rate) is necessary for a unified monetary perspective. For example, assuming an exchange rate of 1 NZD ≈ 4.8 RMB, the converted advisor labor cost would be approximately 40,214.4 RMB, resulting in a total project budget of approximately 41,214.4 RMB.

11.3.3 Budget Control Measures

Resource Costs: Priority will be given to using core resources provided by the client, such as high-performance computers and datasets. Backup resources like cloud GPU rental will only be activated in emergencies to avoid unnecessary expenses.

Advisor Labor Costs: The team will proactively identify technical challenges to improve communication efficiency and reduce repetitive inquiries, ensuring advisor hours are precisely utilized for core work components and preventing wastage.

A budget monitoring mechanism will be established, where the team leader regularly reviews cost expenditures. If risks of exceeding the budget arise, team meetings will be promptly convened to adjust plans, ensuring project costs remain manageable.

Disclaimer:

Clients should note the general basis upon which the Auckland University of Technology undertakes its student projects on behalf of external sponsors:

While all due care and diligence will be expected to be taken by the students, (acting in software development, research or other IT professional capacities), and the Auckland University of Technology, and student efforts will be supervised by experienced AUT lecturers, it must be recognised that these projects are undertaken in the course of student instruction. There is therefore no guarantee that students will succeed in their efforts.

This inherently means that the client assumes a degree of risk. This is part of an arrangement, which is intended to be of mutual benefit. On completion of the project it is hoped that the client will receive a professionally documented and soundly constructed working software application, some part thereof, or other appropriate set of IT artefacts, while the students are exposed to live external environments and problems, in a realistic project and customer context.

In consequence of the above, the students, acting in their assigned professional capacities and the Auckland University of Technology, disclaim responsibility and offer no warranty in respect of the "technology solution" or services delivered, (e.g. a "software application" and its associated documentation),both in relation to their use and results from their use.

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