VISVESVARAYA TECHNOLOGICAL UNIVERSITY

BELAGAVI

Project Work Phase-I Report on

QUANTUM MACHINE LEARNING FOR PREDICTING BRAIN-COMPUTER INTERFACE (BCI) SIGNALS

Submitted by

Keerti Sudhir Mole	**4BB22AI008**
Noor Fathima	**4BB22AI016**
Pavithra T J	**4BB22AI018**
Sneha L B	**4BB22AI025**

In partial fulfillment of the requirement for the award of the Bachelor Degree In

Artificial Intelligence and Machine Learning

Under the Guidance of

Mr. Shreyan Jain. B.E., M.Tech.

Assistant Professor

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING
Bahubali College of Engineering
Shravanabelagola-573 135

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BAHUBALI COLLEGE OF ENGINEERING

Shravanabelagola-573135

DEPARTMENT OF INFORMATION SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Project Work Phase-1 entitled **"QUANTUM MACHINE LEARNING FOR PREDICTING BRAIN-COMPUTER INTERFACE (BCI) SIGNALS"** is work carried out by bonafied students of Bahubali College of Engineering, **KEERTI SUDHIR MOLE.** USN **4BB22AI008, NOOR FATHIMA.** USN **4BB22AI016, PAVITHRA T J.** USN **4BB22AI018, SNEHA L B.** USN **4BB22AI025** in partial fulfillment of VI Semester to award the Bachelor Degree in **Artificial Intelligence and Machine Learning** of the Visvesvaraya Technological University, Belagavi during the year **2024-25**. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report and deposited in the department library. The Project Phase-I Report has been approved as it satisfies all the academic requirements in respect of Project Work Phase-I prescribed for the Bachelor of Engineering Degree.

Mr. Shreyan Jain Asst. Prof. & Guide. Dept. of AI & ML	**Mrs. Shylaja L N** Asso. Prof. & HOD Dept. of AI& ML	**Dr. Sunil Kumar D** Principal

Name of the Examiners **Signature with Date**

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KEERTI SUDHIR MOLE.
NOOR FATHIMA.
PAVITHRA T J.
SNEHA L B.

ABSTRACT

Brain-Computer Interfaces (BCIs) enable direct communication between the human brain and external devices, offering transformative applications in neuroprosthetics, healthcare, and assistive technologies. However, accurately interpreting brain signals such as Electroencephalography (EEG) remains a significant computational challenge due to their high dimensionality, non-linearity, and noise. This project explores the integration of **Quantum Machine Learning (QML)** techniques to enhance the prediction and classification of brain signals, leveraging the computational power of quantum systems to overcome limitations of classical approaches.

By utilizing quantum algorithms such as the **Quantum Support Vector Machine (QSVM)** and **Variational Quantum Classifiers (VQC)**, we aim to process and learn from EEG data more efficiently and with potentially higher accuracy. The framework employs **Qiskit**, an open-source quantum computing library, to simulate quantum circuits and train models on preprocessed EEG datasets. The model's performance is benchmarked against classical machine learning counterparts to assess improvements in prediction accuracy and computational efficiency.

This fusion of quantum computing and brain signal processing marks a promising direction toward faster, more accurate, and resource-efficient BCI systems, paving the way for future real-time neuroadaptive applications.

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CHAPTER 1

INTRODUCTION

The integration of artificial intelligence with neuroscience has led to remarkable advancements in Brain-Computer Interface (BCI) systems, enabling direct communication between the human brain and external devices. BCI systems analyze brain signals, especially Electroencephalography (EEG), to interpret user intentions and facilitate applications ranging from neuroprosthetics to cognitive monitoring. However, traditional machine learning techniques face limitations in handling the complex, high-dimensional, and noisy nature of EEG data. This is where **Quantum Machine Learning (QML)** offers a transformative potential.

Quantum Machine Learning leverages the principles of quantum computing—such as superposition, entanglement, and quantum parallelism—to enhance the performance of classical algorithms. In recent years, researchers have begun applying QML models to biomedical signal processing, including EEG data, showing promise in improving both accuracy and computational efficiency.

This project focuses on implementing Quantum Machine Learning techniques to predict and classify BCI signals. The core idea is to employ quantum-enhanced algorithms, such as Quantum Support Vector Machines (QSVM) and Quantum Neural Networks (QNN), to extract meaningful patterns from EEG signals. By mapping EEG data into high-dimensional quantum Hilbert spaces, QML can achieve superior generalization and faster learning compared to conventional approaches.

The proposed system aims to overcome the limitations of classical methods—such as poor generalization with limited data, slow processing speed, and low accuracy in signal classification—by introducing quantum models that can process complex, non-linear EEG patterns more effectively. The project also explores the feasibility of hybrid classical-quantum models to bridge the gap between current quantum hardware limitations and practical application needs.

1.1 AIM

The primary aim of this project is to explore the potential of quantum machine learning techniques in predicting Brain-Computer Interface (BCI) signals based on historical data. The project seeks to enhance the accuracy, and efficiency of signal prediction, which is crucial for applications such as neuroprosthetics, brainwave-controlled devices, and cognitive neuroscience research.

1.2 SCOPE

BCI Data Analysis: Using historical brain signal data collected from EEG, EcoG. Quantum Computing Integration: Implementing quantum-based machine learning algorithms to process and predict BCI signals.

Comparison with Classical Machine Learning: Benchmarking the performance of QML against traditional deep learning models.

1.3 OBJECTIVES

- **To** Gather and preprocess historical BCI signal data.
- **To Feature Extraction:** Identify critical features from brain signals that are useful for prediction.
- **To Performance Evaluation:** Compare QML models with classical deep learning approaches such as CNNs and LSTMs.
- **To Optimization:** Improve model efficiency by leveraging quantum computing advantages.
- **To Application Testing:** Validate the model on real-world use cases such as neuroprosthetics and brainwave-based control.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY PAPERS

2.1.1 An Evaluation of Quantum Neural Networks in the Detection of Epileptic Seizures the Neontal Electroenecephalogram

Author Name: N.B. Karayiannis, G. Purushothaman.

Year: 2006 in soft computing

Quantum Neural Networks (QNNs) in detecting epileptic seizures using neonatal EEG (electroencephalogram) recordings. The neonatal EEG data is known for its high variability and noise, making seizure detection a complex problem. Traditional neural networks like feedforward neural networks (FFNNs) have been applied in this domain, but they often struggle with accurately modeling uncertainty in data.

The QNN architecture used in this study is based on principles inspired by quantum theory, particularly in its ability to represent uncertainty through probabilistic interpretation and interference patterns. This is contrasted with FFNNs, which typically rely on deterministic mappings.

Both types of networks were trained to identify short EEG signal segments associated with seizure activity. The training involved feeding the networks with labeled segments and evaluating their ability to generalize to unseen data. One of the central aims of the study was to investigate how each network represents uncertainty and how this impacts the reliability of their outputs in a clinical context.

2.1.2 Quantum Neural Network Based EEG Filtering for a BCI

Author Name: Harish Yeluri.

Year: 2014

This research introduces a novel neural information processing architecture inspired by quantum mechanics, specifically incorporating the Schrödinger wave equation. The proposed architecture, referred to as a recurrent quantum neural network (RQNN), is designed to characterize nonstationary stochastic signals as time-varying wave packets. A robust unsupervised learning algorithm enables the RQNN to effectively capture the statistical behavior of the input signal and facilitates the estimation of signals embedded in noise with unknown characteristics.

The RQNN filtering procedure was applied in a two-class motor imagery-based brain–computer interface (BCI), aiming to filter electroencephalogram (EEG) signals before feature extraction and classification to increase signal separability. A two-step inner–outer fivefold cross-validation approach was utilized to select the algorithm parameters subject-specifically for nine subjects. The study demonstrated that subject-specific RQNN EEG filtering significantly improves BCI performance compared to using only raw EEG or Savitzky–Golay filtered EEG across multiple sessions.

2.1.3 Transfer Learning for EEG Based Brain Computer Interface

Author Name: Dongrui Wu, Yifan Xu, Bao-Liang Lu.

Year: 2020

This work presents a comprehensive review of how **transfer learning (TL)** has been applied in the field of EEG-based brain–computer interfaces (BCIs). BCIs face a major challenge due to the variability in EEG signals, which can differ significantly from one person to another, from session to session, or even when using different devices or performing slightly different tasks. This variability typically requires extensive subject-specific calibration, making BCI systems less practical for real-world applications.

To overcome this issue, the authors explore how transfer learning—where knowledge from related but different domains is reused—can help reduce or eliminate the need for repeated calibrations. They systematically review the application of TL in several types of BCI paradigms, including motor imagery (MI), event-related potentials (ERP), steady-state visual evoked potentials (SSVEP), affective BCIs, regression-based BCI tasks, and even adversarial attacks on BCI systems.

2.1.4 Quantum Machine Learning Application in the Biomedical System

Author Name: D. Maheshwari et al.

Year: 2022

This comprehensive review explores the integration of quantum machine learning (QML) techniques within the biomedical field. It systematically examines various QML algorithms applied to biomedical data, highlighting their potential advantages over classical methods in terms of computational efficiency and accuracy. The study also discusses the challenges faced in implementing QML in real-world biomedical applications, such as data encoding complexities and hardware limitations.

The authors emphasize the transformative potential of QML in areas like medical imaging, genomics, and personalized medicine, while also calling attention to the need for further research to overcome existing hurdles and fully realize the benefits of quantum computing in healthcare.

2.1.5 Quantum Computing and AI in Healthcare

Author Name: Hassan Ali.

Year: 2023

This work explores the integration of quantum computing and artificial intelligence (AI) to address computational challenges in healthcare. It highlights how quantum machine learning (QML) can enhance AI-driven molecular dynamics simulations, facilitating more efficient drug discovery processes. The paper also discusses the application of quantum-assisted deep learning models to better understand complex biological processes, such as protein folding and metabolic pathway linkages, which can improve disease progression prediction and therapeutic target discovery.

Furthermore, the study examines the potential of quantum computing to process large and complex biological datasets more effectively than traditional computing methods, thereby accelerating biomedical research and the development of personalized medicine. It emphasizes the transformative impact of combining quantum computing with AI in revolutionizing genetic data processing and medication development.

only boosts the prediction performance, but also alleviates the problem of new item cold start.

2.1.6 QML Applied to the Classification of ERP

Author Name: Grrgorie Catten, Anton Andrew.

Year: 2023

This research explores the application of quantum machine learning (QML) techniques, specifically a **Quantum Support Vector Classifier (QSVC)**, to classify event-related potentials (ERPs) derived from electroencephalography (EEG) data. ERPs are brain responses that are time-locked to specific sensory, cognitive, or motor events and are commonly used in brain-computer interface (BCI) systems.

The study aimed to assess the feasibility of using QSVC for ERP classification, addressing the challenge of low information transfer rates in non-invasive EEG-based BCIs. The QSVC model achieved a training balanced accuracy of **83.17%**, indicating its capability to learn from EEG data. However, the prediction balanced accuracy was **50.25%**, suggesting that while the model could learn patterns during training, its generalization to unseen data was limited. The authors noted that further research, including better configuration of the classifier and increasing the number of quantum circuit executions (shots), is necessary to enhance predictive performance.

2.1.7 Quantum Machine Learning for Biomedical Data Analysis

Author Name: D. Gowda V., H. Y. Patil, S. Suneetha.

Year: 2024

This work explores the intersection of quantum computing and machine learning as applied to biomedical data. It begins by explaining the fundamental principles of quantum physics and machine learning, providing a foundation for understanding how these fields combine. The authors emphasize that quantum machine learning has the potential to handle large, complex biomedical datasets more efficiently than traditional computing, due to the unique properties of quantum systems such as superposition and entanglement.

The chapter covers several applications where quantum machine learning can bring transformative changes. These include predicting protein folding, analyzing genomic data, and enhancing real-time diagnostics. By leveraging quantum algorithms, these tasks can potentially be performed faster and with greater accuracy, which could revolutionize biomedical research and healthcare delivery.

The authors also address some challenges, both technical and ethical, that arise when implementing quantum machine learning in biomedical contexts. Despite these challenges, the chapter concludes on an optimistic note, highlighting the promising future of quantum-powered machine learning as a powerful tool in advancing biomedical science and improving healthcare outcomes.

The chapter discusses how quantum algorithms can process vast and complex biomedical datasets more efficiently than classical methods, leveraging properties like superposition and entanglement.

2.1.8 QML Based Decision Support System for the Detection of BCI signals from EEG Records

Author Name: J. Han, M. Kamber. J. Pei.

Year: 2024

This study explores the application of quantum machine learning (QML) techniques, specifically Quantum Support Vector Machines (QSVM), to classify electroencephalography (EEG) signals for the early detection of schizophrenia. The researchers utilized EEG data from four channels, applying Principal Component Analysis (PCA) for dimensionality reduction and transforming the data into qubit form using various feature maps. The QSVM algorithm was then employed with different qubit numbers and circuits, alongside classical machine learning algorithms, to evaluate performance.

The findings revealed that the QSVM algorithm achieved a 100% success rate in classifying the EEG dataset when using Pauli X and Pauli Z feature maps. This result suggests that quantum classifiers can effectively generalize on EEG data, potentially offering a complementary approach to classical methods in the diagnosis of schizophrenia.

2.1.9 QML for Enhanced EEG Encoding

Author Name: Chi Shenf Chen, Samuel Yen-Chin Chen.

Year: 2024

This study introduces **QEEGNet**, a hybrid neural network that integrates quantum machine learning (QML) techniques with the classical EEGNet architecture to enhance the encoding and analysis of electroencephalography (EEG) signals. Traditional EEG analysis methods often rely on classical machine learning and deep learning techniques, such as EEGNet, which have demonstrated significant success in various EEG-based tasks. However, these models sometimes face limitations in capturing the complex and high-dimensional nature of EEG signals.

QEEGNet addresses these challenges by incorporating quantum layers into the neural network, allowing it to capture more intricate patterns in EEG data and potentially offering computational advantages. The authors evaluate QEEGNet on the BCI Competition IV 2a dataset, demonstrating that it consistently outperforms traditional EEGNet on most subjects and exhibits improved robustness to noise. These findings highlight the significant potential of quantum-enhanced neural networks in EEG analysis, suggesting new directions for both research and practical applications in the field.

2.1.10 Quantum Deep Learning in Neuroinformatics

Author Name: Lins et al.

Year: 2025

This systematic review aims to evaluate the efficacy of quantum deep learning (QDL) models in neuroinformatics, specifically as opposed to classical deep learning approaches. The authors conducted a statistical analysis of various studies, including tumor classification, Alzheimer's diagnosis, stroke lesion detection, cognitive state monitoring, and brain age prediction. The results indicated that QDL models achieved a mean accuracy of 0.9701, slightly outperforming classical models with a mean accuracy of 0.9650. QDL also demonstrated better performance in metrics such as F1-score, dice coefficient, and RMSE.

The review discusses the current state of neuroinformatics and where QDL stands relative to recent advancements. It highlights the potential of QDL in healthcare applications as quantum technology evolves and outlines existing research gaps to encourage further investigation in this developing field.

2.2 DRAWBACKS OF EXISTING SYSTEM:

- Quantum computing hardware is still immature, with limited qubits, short coherence times, and high error rates, restricting model complexity and scale.
- QML models often show good training accuracy but have poor generalization on new, unseen BCI data, affecting robustness.
- There is no standardized, effective method for encoding EEG/BCI signals into quantum feature spaces, leading to inconsistent performance.
- Quantum models tend to be “black boxes,” lacking interpretability, which limits user trust and clinical acceptance.
- Scalability issues arise when applying QML to large, high-dimensional EEG datasets common in BCI applications
- The quantum software ecosystem is still developing, requiring specialized expertise and limiting accessibility.

2.3 ADVANTAGES OF PROPOSED SYSTEM

- To improve prediction accuracy by capturing complex patterns in EEG signals beyond classical methods.

- To enhance feature representation through quantum feature mapping for richer encoding of brain data.
- To ensure better generalization and reduce overfitting on unseen BCI data.
- To efficiently process high-dimensional EEG datasets using quantum parallelism.
- To optimize performance by combining quantum and classical computing in a hybrid architecture.
- To reduce training and inference time, enabling faster computation for real-time BCI applications.
- To provide a scalable framework adaptable to future advances in quantum hardware.
- To introduce innovative quantum technology that could lead to breakthroughs in brain-computer interface research.

CHAPTER 3

REQUIREMENT SPECIFICATION

Requirements are the key for the successful completion of the project. Any software development can give the correct result on time only if the requirements have been well understood. The requirement can be said as the heart of the software cycle.

3.1 INPUT REQUIREMENTS

Graph-Based (Time-Series Data from EEG Signals).

3.2 OUTPUT REQUIREMENTS

Text-Based Labels (Predicted Brain States or Commands).

3.3 FUNCTIONAL REQUIREMENT

Functional Requirement defines a function of a software system and how the system must behave when presented with specific inputs or conditions. These may include calculations, data manipulation and processing and other specific functionality. In this system following are the functional requirements: -

Client side

- Upload EEG Data
  The client application must allow users to upload EEG signal data files (e.g., `.csv`, `.edf`) manually or stream from an EEG device. The system shall support real-time or batch-mode data input.
- Request Brain State Prediction
  The client must allow users to initiate a prediction request based on the uploaded EEG data. The system must send this request to the server, including necessary preprocessed features
- Visualize EEG Signals
  The client shall visualize raw EEG signals in a graphical form (line plots per channel) for verification.

Server Side

- Handle EEG Input Requests

  The server must receive EEG data from the client, verify its format, and initiate preprocessing and feature extraction.

- Preprocess and Normalize Eeg Signals

  The Sever must perform signal filtering, noise/artifact removal (e.g., ICA), and standardization before passing data to the model.

- Extraxt Features for Model Input

  The Server shall extract time-domain and frequency-domain features from EEG data. These features must be encoded into quantum-readable formats using quantum feature maps.

- Quantum Model OInference

  The server must process the input using a Quantum Machine Learning model (e.g., QSVM, VQC) to predict the brain state.

3.4 NON-FUNCTIONAL REQUIREMENT:

Availability

- This is a **web-based application** utilizing Quantum Machine Learning (QML) approaches, available for access by all registered users.
- The application shall be **compatible with all major web browsers**, including Chrome, Firefox, Safari, and Edge.
- The system should be available **24/7**, except during scheduled maintenance.The application may optionally help users track model usage and predictions for transperency.

Security

- All EEG data and user information are securely stored on the server using **role-based access control (RBAC)**.
- **Authentication mechanisms** (e.g., login credentials or tokens) shall protect user-specific sessions.
- Sensitive data transmission shall be **encrypted using HTTPS**.
- Unauthorized access to stored EEG data, model predictions, and analytics will be **strictly prohibited** and monitored.

Reliability

- The system shall be designed to provide **high reliability**, with minimal downtime.
- Reliability shall be measured using **Mean Time Between Failures (MTBF)**.
- **Failure detection mechanisms** will be integrated to notify admins in case of errors.
- **Backup systems and logs** shall be maintained to recover data in case of system failures.

HARDWARE REQUIREMENTS:

- System Processor : Multi-Core Processors.
- RAM : Min 16GB/32GB.
- Operating System : Windows.
- Simulator : Cloud based simulator.

SOFTWARE REQUIREMENTS:

- Frontend : React, html, Java Script, React Rooter.
- Backend :
  - Programming Language : Python.
  - ML Algorithm : litraries.
  - Libraries : Pennylane, Tensorflow quantum, Skitlearn, Pandas, numpy, Matplotlib, Seaborn.

CHAPTER 4

METHODOLOGY:

- **Data Acquisition:** Collect historical EEG/ECoG data from open-source datasets or experimental studies. Perform signal preprocessing (artifact removal, normalization, and segmentation).
- **Feature Extraction:** Apply techniques like wavelet transforms or Fourier analysis to extract meaningful signal patterns.
- **Quantum Machine Learning Model Development**: Implement Quantum Neural Networks (QNN), QSVM, or Quantum Boltzmann Machines. Use quantum feature maps to encode BCI signals into quantum states. Train models using quantum computing frameworks (Qiskit, TensorFlow Quantum)
- **Model Training and Evaluation:** Train models using classical and quantum methods. Compare accuracy, processing time, and computational efficiency

4.2 RESULTS EXPECTED:

Improved accuracy in predicting BCI signals using QML compared to classical approaches. Faster processing of brain signals due to quantum parallelism. Enhanced feature recognition from complex neural patterns. Potential for real-time applications in neuroprosthetics and brain controlled interfaces.

REFERENCES

[1] Dongrui Wu, Yifan Xu, Bao-Liang Lu. ” Transfer Learning for EEG-Based Brain-Computer Interfaces”. https://bcmi.sjtu.edu.cn/~blu/papers/2020/2020-9.pdf

[2] D. Maheshwari, B. Garcia-Zapirain, D. Sierra-Sosa. “Quantum Machine Learning Applications in the Biomedical Domain”. https://www.researchgate.net/publication/362356293_Quantum_Machine_Learning_applications_in_the_Biomedical_domain_A_Systematic_Review

[3] D. Gowda V., H. Y. Patil, S. Suneetha. “Quantum Machine Learning for Biomedical Data Analysis”. https://www.giet.edu/wp-content/uploads/2024/08/Pubication1.pdf

[4] Hassan Ali . “Quantum Computing and AI in Healthcare”. https://www.researchgate.net/publication/389254431_Quantum_computing_and_AI_in_healthcare_Accelerating_complex_biological_simulations_genomic_data_processing_and_drug_discovery_innovations

[5] J. Han, M. Kamber, J. Pei.” Quantum Machine-Based Decision Support System for the Detection of Schizophrenia from EEG Records”. https://www.researchgate.net/publication/378743221_Quantum_Machine-Based_Decision_Support_System_for_the_Detection_of_Schizophrenia_from_EEG_Records

[6] Chi-Sheng Chen, Samuel Yen-Chi Chen, Aidan Hung-Wen Tsai, Chun-Shu Wei “QEEGNet: Quantum Machine Learning for Enhanced Electroencephalography Encoding”.

[7] Nabil Anan Orka, Md. Abdul Awal. “Quantum Deep Learning in Neuroinformatics”. https://link.springer.com/article/10.1007/s10462-025-11136-7

[8] Grégoire Cattan, Alexandre Quemy, Anton Andreev. “First Steps Towards Quantum Machine Learning Applied to the Classification of Event-Related Potentials”. https://arxiv.org/abs/2302.02648

[9] Chi-Sheng Chen, Samuel Yen-Chi Chen, Aidan Hung-Wen Tsai, Chun-Shu Wei. “Quantum Machine Learning for Enhanced Electroencephalography Encoding”. https://arxiv.org/abs/2407.19214

[10] Nabil Anan Orka, Md. Abdul Awal. “Quantum Deep Learning in Neuroinformatics”. https://link.springer.com/article/10.1007/s10462-025-11136-7?utm_source

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S. No	Activities	Resources Req. (4 M's)				Depen dency	No. of Days	% comp	Feb-19		March-31				April-30				May-31			
		Men	Mat	M/C	Money				w4	w5	w1	w2	w3	w4	w1	w2	w3	w4	w1	w2	w3	w4
1	Group formation	✓					**1**	**1%**														
2	Guide allotment and meeting	✓				1	**16**	**13%**														
3	Finalization of project title	✓				2	**14**	**12%**														
4	Synopsis preparation	✓	✓	✓		3	**4**	**3%**														
5	Synopsis correction with guide	✓	✓	✓		2	**2**	**2%**														
6	Project synopsis submission	✓	✓		✓	4	**4**	**3%**														
7	Slide preparation for synopsis	✓	✓	✓		3	**6**	**5%**														
8	Synopsis phase seminar	✓	✓	✓			**1**	**1%**														
9	Literature survey	✓	✓	✓		3	**5**	**4%**														
10	Draft copy of first phase report	✓	✓	✓	✓	3	**2**	**2%**														
11	Submission of first phase report	✓	✓		✓	10	**4**	**3%**														
12	Slide preparation for phase1	✓	✓	✓		3	**1**	**1%**														
13	First phase seminar	✓	✓	✓		12	**2**	**2%**														
14	Report Correction From the guide	✓	✓	✓		2	**3**	**3%**														
15	Take hard Copy of Phase-1Report	✓	✓	✓	✓	14	**1**	**1%**														
16	Signature for the Hard Copy from Principal	✓	✓			15		**13%**														
17	Submission of Phase-1Report	✓	✓			15	**3**	**3%**														