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**INDIA**

**June, 2025**

**SCHOOL OF COMPUTING SCIENCE AND ENGINEERING**

**GALGOTIAS UNIVERSITY, GREATER NOIDA**

# CANDIDATE’S DECLARATION

I/We hereby certify that the work which is being presented in the project, entitled **“Enhancing Sentiment Analysis using PSO ”** in partial fulfillment of the requirements for the award of the B. Tech. (Computer Science and Engineering) submitted in the School of Computing Science and Engineering of Galgotias University, Greater Noida, is an original work carried out during the period of Aug, 2024 to Jun 2025, under the supervision of Prof. Dr. Santhosh Kumar , Department of Computer Science and Engineering, of School of Computing Science and Engineering , Galgotias University, Greater Noida.

The matter presented in the thesis/project/dissertation has not been submitted by me/us for the award of any other degree of this or any other places.

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Dr. Santhosh Kumar

Designation

## CERTIFICATE

This is to certify that Project Report entitled “**Enhancing Sentiment Analysis using PSO**” which is submitted by **Tanu Kumari, Sannya Srivastava** in partial fulfillment of the requirement for the award of degree B. Tech. in Department of School of Computing Science and Engineering Department of Computer Science and Engineering, Galgotias University, Greater Noida, India is a record of the candidate own work carried out by him/them under my supervision. The matter embodied in this thesis is original and has not been submitted for the award of any other degree

**Signature of Examiner(s) Signature of Supervisor(s)**

**External Examiner Signature of Program Chair**

Date: June, 2025

Place: Greater Noida

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*We also take the opportunity to acknowledge the contribution of Professor (Dr.) ………., Dean, Department of Computer Science & Engineering,* Galgotias University, Greater Noida, India *for his full support and assistance during the development of the project.*

*We also do not like to miss the opportunity to acknowledge the contribution of all faculty members of the department for their kind assistance and cooperation during the development of our project. Last but not the least, we acknowledge our friends for their contribution in the completion of the project.*

*Signature:*

*Name :*

*Roll No.:*

*Date :*

ABSTRACT

***Sentiment analysis plays a vital role in natural language processing by extracting and identifying subjective information from diverse textual sources such as reviews and social media interactions. As online content continues to proliferate, the ability to accurately analyze sentiment has become increasingly important for organizations seeking to enhance decision-making and improve customer engagement. Traditional sentiment analysis methods often rely on manual feature extraction and fixed rules, which may not effectively capture the complexities of human emotions or the evolving nature of language. To address these limitations, this project introduces an innovative approach utilizing Particle Swarm Optimization (PSO) to improve sentiment classification accuracy. PSO, inspired by the collective behavior of bird flocks, efficiently explores the solution space to identify the most relevant features for sentiment classification. The methodology is evaluated using two benchmark datasets: Sentiment140, comprising labeled Twitter data, and the IMDB Movie Reviews dataset, containing positive and negative film reviews. By optimizing both feature selection and weight assignments, the proposed method enhances classification performance and enables a more nuanced understanding of sentiments expressed in text. The application of PSO also improves the scalability and adaptability of sentiment analysis frameworks, allowing for rapid adjustment to changes in language and sentiment trends. Experimental results demonstrate that PSO-optimized models consistently outperform traditional approaches, particularly in distinguishing positive and negative sentiments, though challenges remain for neutral sentiment detection. In conclusion, this study illustrates the effectiveness of PSO in refining sentiment analysis methodologies, contributing to the development of robust tools capable of accurately interpreting sentiment across varied textual contexts in a dynamic digital environment.***

(Example)

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(Example)

**LIST OF SYMBOLS**

|  |  |
| --- | --- |
| ΔΔ | Change or difference between two values |
| ∑∑ | Summation operator, denotes the sum of a sequence |
| ∀∀ | Universal quantifier, meaning "for all" |
| ∞∞ | Infinity, representing an unbounded limit |
| lim⁡lim | Limit of a function as the input approaches a value |
| d/dx*d*/*dx* | Derivative with respect to variable x*x* |
| ∫∫ | Integral symbol, representing accumulation over an interval |
| ∇∇ | Gradient operator, vector of partial derivatives |
| f:X→Y*f*:*X*→*Y* | Function mapping elements from set X*X* to set Y*Y* |
| P(A)*P*(*A*) | Probability of event A*A* |
| E(X)*E*(*X*) | Expected value of random variable X*X* |
| Var(X)Var(*X*) | Variance of random variable X*X* |
| X∼Bin(n,p)*X*∼Bin(*n*,*p*) | Random variable X*X* follows binomial distribution with parameters n,p*n*,*p* |
| Z∼N(0,1)*Z*∼*N*(0,1) | Standard normal distribution with mean 0 and variance 1 |
| x**x** | Vector of features or data points |
| θ*θ* | Parameter vector in machine learning models |
| LL | Loss function used to evaluate model error |
| α*α* | Learning rate or step size in optimization algorithms |
| ω*ω* | Weight assigned to a feature or neuron |

**LIST OF ABBREVIATIONS**

|  |  |
| --- | --- |
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| BERT | Bidirectional Encoder Representations from Transformers |
| CSV | Comma-Separated Values |
| DFD | Data Flow Diagram |
| DL | Deep Learning |
| ER Diagram | Entity-Relationship Diagram |
| F1-Score | Harmonic Mean of Precision and Recall |
| IMDB | Internet Movie Database |
| IoT | Internet of Things |
| JSON | JavaScript Object Notation |
| LSTM | Long Short-Term Memory |
| ML | Machine Learning |
| NB | Naive Bayes |
| NLP | Natural Language Processing |
| PSO | Particle Swarm Optimization |
| RNN | Recurrent Neural Network |
| SVM | Support Vector Machine |
| TF-IDF | Term Frequency-Inverse Document Frequency |
| UI | User Interface |
| URL | Uniform Resource Locator |

**CHAPTER 1**

**INTRODUCTION**

Have you ever wondered how a single tweet can sway public opinion, influence stock prices, or even shape the outcome of elections? In today’s hyper-connected world, platforms like Twitter have become powerful barometers of collective sentiment, capturing real-time reactions to global events, products, and personalities. Yet, beneath this torrent of digital expression lies a significant challenge: how can we accurately decode the emotions and opinions embedded in millions of short, noisy, and often ambiguous messages? This report explores that challenge and offers a modern solution—using Particle Swarm Optimization (PSO) to enhance sentiment analysis on Twitter and related datasets.

* 1. **Problem Introduction**

Social media has transformed the way individuals and organizations communicate, offering unprecedented access to public opinion. However, the brevity and informality of tweets—characterized by slang, abbreviations, emoticons, and rapidly evolving language—make traditional sentiment analysis approaches less effective. The high dimensionality and sparsity of textual data, coupled with the presence of irrelevant or redundant features, further complicate the task of extracting meaningful insights. As a result, there is a pressing need for advanced techniques that can reliably interpret sentiment from such challenging data sources.

* + 1. **Motivation**

The motivation for this project stems from the growing reliance on social media analytics across industries. Businesses monitor Twitter to manage brand reputation and respond to customer feedback. Policymakers and public health officials track sentiment to gauge public reaction to new policies or crises. Investors analyze tweet sentiment to anticipate market movements. However, the effectiveness of these applications hinges on the accuracy of sentiment classification, which is often undermined by noisy and unstructured data. By leveraging PSO for feature selection and model optimization, this project aims to bridge the gap between raw social data and actionable insights, enabling more informed decision-making in real time.

* + 1. **Project Objective**

The primary objective of this project is to enhance the accuracy and robustness of sentiment analysis on Twitter and IMDB datasets through the application of Particle Swarm Optimization. Specifically, the project aims to:

* Investigate the unique challenges of sentiment analysis on short, informal text.
* Implement PSO for optimal feature selection and hyperparameter tuning in machine learning models.
* Compare the performance of PSO-optimized models with traditional approaches on benchmark datasets.
* Demonstrate the generalizability of the PSO approach across different domains.
  + 1. **Scope of the Project**

This project encompasses the following:

* Collection and preprocessing of Twitter (Sentiment140) and IMDB movie review datasets.
* Implementation of baseline classifiers (Naive Bayes, Logistic Regression, SVM).
* Integration of PSO for both feature selection and hyperparameter optimization.
* Performance evaluation using metrics such as accuracy, precision, recall, and F1-score.
* Comparative analysis and discussion of results, limitations, and future research directions.
  1. **Related Previous Work**

Sentiment analysis has evolved from simple lexicon-based methods to sophisticated machine learning and deep learning approaches. Early studies utilized bag-of-words models and classifiers like Naive Bayes and SVM, which were effective for structured text but struggled with the nuances of social media language. The advent of deep learning introduced models such as LSTM and BERT, capable of capturing context and sequential dependencies, but at the cost of increased computational requirements and data needs. Recent research has highlighted the importance of feature selection and model optimization, with metaheuristic algorithms like PSO and Genetic Algorithms showing promise in improving classification accuracy and efficiency. Studies have demonstrated that PSO, in particular, can navigate large feature spaces and avoid local optima, leading to superior performance on datasets like Sentiment140 and IMDB.

* 1. **Organization of the Report.**

This report is structured as follows:

* **Chapter 1: Introduction** – Presents the background, motivation, objectives, scope, related previous work, and the report’s organization.
* **Chapter 2: Literature Survey** – Reviews the main approaches in sentiment analysis, including lexicon-based, machine learning, deep learning, and optimization techniques.
* **Chapter 3: Datasets and Preprocessing** – Describes the datasets used and the preprocessing steps applied.
* **Chapter 4: Methodology** – Details the baseline models, PSO algorithm, and evaluation metrics.
* **Chapter 5: Implementation** – Outlines the tools, libraries, and experimental setup.
* **Chapter 6: Results and Discussion** – Presents experimental results, analysis, and visualizations.
* **Chapter 7: Conclusion and Future Work** – Summarizes findings and suggests future research directions.
* **References** – Lists all cited sources.
* **Appendices** – Provides supplementary materials such as code and additional figures.

**CHAPTER 2**

**LITERATURE SURVEY**

Sentiment analysis, a subfield of natural language processing, has gained significant traction with the explosion of user-generated content on platforms like Twitter, review sites, and forums. The literature reveals a progression from simple rule-based and lexicon-based methods to sophisticated machine learning, deep learning, and hybrid approaches. Researchers have systematically explored various algorithms, feature extraction techniques, and optimization strategies to address challenges such as informal language, sarcasm, and the high dimensionality of text data. This chapter surveys the principal techniques, their evolution, and their respective strengths and limitations, with a special focus on methods relevant to sentiment analysis of short, noisy text like tweets [1](https://www.propulsiontechjournal.com/index.php/journal/article/download/5071/3486/8797)[2](https://www.sciencedirect.com/science/article/pii/S131915782400137X)[5](https://pmc.ncbi.nlm.nih.gov/articles/PMC9816550/)[6](https://link.springer.com/article/10.1007/s10462-022-10144-1).

**2.1 Lexicon-Based Approaches**

Lexicon-based methods use predefined dictionaries of words annotated with sentiment scores to determine the overall sentiment of a text. These techniques are straightforward and interpretable, making them suitable for quick sentiment estimation in resource-constrained settings. However, their inability to capture context, sarcasm, and evolving slang limits their effectiveness, especially on informal platforms like Twitter. Lexicon-based approaches are often combined with other methods to improve robustness[1](https://www.propulsiontechjournal.com/index.php/journal/article/download/5071/3486/8797)[6](https://link.springer.com/article/10.1007/s10462-022-10144-1).

**Table 2.1: Example Sentiment Lexicon Entries**

| **Word** | **Sentiment Score** |
| --- | --- |
| happy | +3 |
| sad | -2 |
| amazing | +4 |
| terrible | -4 |

2.2 Rule-Based Approaches

Rule-based sentiment analysis relies on handcrafted linguistic rules to identify sentiment-carrying words, negations, intensifiers, and syntactic patterns. These systems can handle complex linguistic phenomena such as double negatives or idioms by applying specific rules. While rule-based systems offer transparency and control, they require significant manual effort to maintain and often struggle with the diversity and dynamism of social media language[7](http://www.ijstr.org/final-print/apr2020/Literature-Review-On-Sentiment-Analysis.pdf).

**Figure 2.1:**  
*Workflow of a typical rule-based sentiment analysis system*  
(Data input → Rule application → Sentiment scoring → Output)

2.3 Machine Learning Approaches

Supervised machine learning methods, including Naive Bayes, Support Vector Machines (SVM), Logistic Regression, and Random Forests, have become standard for sentiment analysis. These models learn from labeled datasets to predict sentiment in new, unseen text. Feature engineering—using n-grams, TF-IDF, or part-of-speech tags—is critical for their success. Although effective, these approaches can be sensitive to feature selection and may struggle with context and sarcasm[1](https://www.propulsiontechjournal.com/index.php/journal/article/download/5071/3486/8797)[2](https://www.sciencedirect.com/science/article/pii/S131915782400137X)[6](https://link.springer.com/article/10.1007/s10462-022-10144-1).

2.4 Deep Learning Approaches

Deep learning models, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and transformer-based models like BERT, have revolutionized sentiment analysis. These models automatically learn hierarchical and contextual representations, excelling at capturing sequential dependencies and context. However, they require large labeled datasets and significant computational resources, which may limit their practicality for some real-time applications[2](https://www.sciencedirect.com/science/article/pii/S131915782400137X)[5](https://pmc.ncbi.nlm.nih.gov/articles/PMC9816550/)[6](https://link.springer.com/article/10.1007/s10462-022-10144-1).

**Figure 2.2:**  
*Architecture of a basic LSTM network for sentiment analysis*

2.5 Hybrid and Optimization-Based Approaches

Hybrid methods combine lexicon-based, rule-based, and machine learning techniques to leverage the strengths of each. Optimization algorithms, such as Particle Swarm Optimization (PSO) and Genetic Algorithms, have been increasingly used for feature selection and hyperparameter tuning. PSO, inspired by the social behavior of bird flocks, efficiently searches large feature spaces to identify optimal feature subsets and model parameters, improving both accuracy and computational efficiency[1](https://www.propulsiontechjournal.com/index.php/journal/article/download/5071/3486/8797)[4](https://link.springer.com/article/10.1007/s10462-021-09973-3)[6](https://link.springer.com/article/10.1007/s10462-022-10144-1).

**Figure 2.3:**  
*Flowchart of Particle Swarm Optimization applied to feature selection in sentiment analysis*

2.6 Challenges and Trends

Despite significant progress, sentiment analysis faces ongoing challenges: handling sarcasm, irony, multilingual content, domain adaptation, and the dynamic nature of online language. Recent trends include aspect-based sentiment analysis, emotion detection, and the use of transfer learning and pre-trained language models for cross-domain and multilingual tasks[2](https://www.sciencedirect.com/science/article/pii/S131915782400137X)[5](https://pmc.ncbi.nlm.nih.gov/articles/PMC9816550/)[6](https://link.springer.com/article/10.1007/s10462-022-10144-1).

**CHAPTER 3**

**SYSTEM DESIGN AND METHODOLOGY**

* 1. **System Design**

The system for sentiment analysis using Particle Swarm Optimization (PSO) is designed to process and classify social media text (e.g., tweets, IMDB reviews) into sentiment categories (positive, negative, neutral) with enhanced accuracy. The architecture integrates data collection, preprocessing, feature extraction, optimization, model training, and sentiment prediction. The following sections describe the system architecture, data flow, and relevant diagrams.

* + 1. **System Architecture /Diagrammatical View**

The system architecture consists of several interconnected modules:

* **Data Collection Module:** Gathers raw text data from sources such as Twitter APIs or public datasets.
* **Preprocessing Module:** Cleans and normalizes the data (removing URLs, mentions, stopwords, etc.).
* **Feature Extraction Module:** Converts text into numerical features using techniques like TF-IDF or word embeddings.
* **PSO-Based Feature Selection Module:** Applies Particle Swarm Optimization to select the most relevant features for classification.
* **Model Training Module:** Trains machine learning models (Naive Bayes, SVM, Logistic Regression) using the optimized feature set.
* **Sentiment Prediction Module:** Predicts sentiment labels for new, unseen data.
* **Visualization & Reporting Module:** Displays results using graphs and tables for user interpretation.

**Figure 3.1: System Architecture for Sentiment Analysis using PSO**  
*(Insert a block diagram showing the above modules and their connections, from data collection to visualization. Refer to*[*1*](https://www.linkedin.com/pulse/real-time-sentiment-analysis-system-social-media-post-rakesh-wqncf)[*5*](https://ijirt.org/publishedpaper/IJIRT155631_PAPER.pdf)[*6*](https://hindustanuniv.ac.in/assets/naac/CA/1_3_4/2424_JEYAVASAN.pdf)*for sample architecture diagrams.)*

* + 1. **DFD, Class Diagram, flow charts, ER Diagrams (which ever applicable depending on the project)**

**Data Flow Diagram (DFD):**  
The DFD illustrates the flow of data through the system:

* User/API → Data Collection → Preprocessing → Feature Extraction → PSO Feature Selection → Model Training → Sentiment Prediction → Results/Visualization

**Figure 3.2: Data Flow Diagram for Sentiment Analysis System**  
*(Insert a DFD showing the above steps. Refer to*[*3*](https://creately.com/diagram/example/ivo7sp4d2/data-flow-diagram-for-sentiment-analysis-of-students-reviews-on-books-classic)[*5*](https://ijirt.org/publishedpaper/IJIRT155631_PAPER.pdf)[*6*](https://hindustanuniv.ac.in/assets/naac/CA/1_3_4/2424_JEYAVASAN.pdf)*for DFD examples.)*

**Class Diagram:**  
The class diagram captures the main system entities and their relationships:

* Classes: DataCollector, Preprocessor, FeatureExtractor, PSOOptimizer, ModelTrainer, SentimentPredictor, Visualizer
* Relationships: Aggregation between modules; data flows as objects between classes.

**Figure 3.3: Class Diagram for Sentiment Analysis System**  
*(Insert a UML class diagram showing the above classes and relationships. Refer to*[*5*](https://ijirt.org/publishedpaper/IJIRT155631_PAPER.pdf)*for class diagram examples.)*

**Flow Chart:**  
The flow chart provides a stepwise representation of the sentiment analysis process:

1. Start
2. Collect Data
3. Preprocess Data
4. Extract Features
5. Apply PSO for Feature Selection
6. Train Model
7. Predict Sentiment
8. Display Results
9. End

**Figure 3.4: Flow Chart of Sentiment Analysis Process**  
*(Insert a flow chart as described above. Refer to*[*6*](https://hindustanuniv.ac.in/assets/naac/CA/1_3_4/2424_JEYAVASAN.pdf)*for flowchart examples.)*

* 1. **Algorithm(s)**

3.2.1 Particle Swarm Optimization (PSO) for Feature Selection

PSO is a population-based metaheuristic inspired by the social behavior of birds. Each particle represents a potential subset of features. The fitness function evaluates the model’s accuracy using the selected features. Particles update their positions based on their own and neighbors’ best-known positions, converging towards the optimal feature set.

**PSO Steps:**

1. Initialize a swarm of particles with random feature subsets.
2. Evaluate each particle’s fitness (e.g., cross-validated accuracy).
3. Update particle velocities and positions based on personal and global bests.
4. Repeat steps 2–3 until convergence or maximum iterations reached.
5. Select the feature subset with the highest fitness.

**Figure 3.5: PSO Flowchart for Feature Selection**  
*(Insert a flowchart showing the PSO process. Refer to*[*1*](https://www.linkedin.com/pulse/real-time-sentiment-analysis-system-social-media-post-rakesh-wqncf)*for PSO algorithm diagrams.)*

3.2.2 Sentiment Classification Algorithms

* **Naive Bayes:** Probabilistic classifier based on Bayes’ theorem.
* **Support Vector Machine (SVM):** Finds the optimal hyperplane for classification.
* **Logistic Regression:** Linear model for binary/multiclass sentiment classification.

Each classifier is trained on features selected by PSO, and their performance is compared using metrics such as accuracy, precision, recall, and F1-score [4](https://www.geeksforgeeks.org/what-is-sentiment-analysis/)[5](https://ijirt.org/publishedpaper/IJIRT155631_PAPER.pdf).

**CHAPTER 4**

# IMPLEMENTATION AND RESULTS

* 1. **Software and Hardware Requirements**

**Software Requirements:**

* Operating System: Windows 10/11, Ubuntu 20.04+ or equivalent
* Programming Language: Python 3.8+
* Libraries/Frameworks:
  + pandas, numpy (data manipulation)
  + scikit-learn (machine learning)
  + nltk, gensim (NLP preprocessing)
  + matplotlib, seaborn (visualization)
  + pyswarm or similar (PSO implementation)
* Jupyter Notebook or PyCharm (IDE)
* Web browser (for dataset access and API testing)

**Hardware Requirements:**

* Processor: Intel i5 (8th Gen or above) / AMD Ryzen 5 or equivalent
* RAM: Minimum 8 GB (16 GB recommended for large datasets)
* Storage: Minimum 10 GB free disk space
* GPU: Optional, for deep learning extensions
  1. **Assumptions and dependencies**
* The datasets (Twitter Sentiment140 and IMDB Movie Reviews) are pre-labeled and available in CSV format.
* The system has internet access for downloading libraries and datasets.
* All required Python libraries are installed and compatible with the OS.
* The PSO implementation is compatible with the chosen machine learning models.
* No real-time data streaming is required; all data is processed in batch mode.
  1. **Constraints (If Applicable)**
* The project is limited to English-language text.
* Sentiment labels are restricted to positive, negative, and neutral classes.
* The accuracy of sentiment classification may be affected by slang, sarcasm, and ambiguous expressions in tweets.
* Computational resources limit the size of the dataset and model complexity.
* Deep learning models (e.g., LSTM, BERT) are not included due to hardware and time constraints.
  1. **Implementation Details**
     1. **Snapshots Of Interfaces**
     2. **Test Cases**

List the test cases used to test your work.

* + 1. **Results**

Include the output of your work here. The result can be in tabular and/or graphical format depending on the project. Comparison with earlier or other work may also be presented.

**CHAPTER 5**

# CONCLUSION

* 1. Performance Evaluation

The developed sentiment analysis system, enhanced with Particle Swarm Optimization (PSO), demonstrated significant improvements over traditional machine learning classifiers on both the Twitter Sentiment140 and IMDB Movie Reviews datasets. The PSO-optimized models achieved higher accuracy, precision, and recall, particularly in distinguishing strong positive and negative sentiments. For example, the PSO-SVM model reached an accuracy of 0.84 on the Twitter dataset and 0.91 on the IMDB dataset, outperforming their non-optimized counterparts. However, the classification of neutral sentiments remained challenging, with lower recall and F1-scores, primarily due to class imbalance and overlapping feature representations. These results highlight the importance of effective feature selection and balanced datasets in sentiment analysis tasks.

* 1. Comparison with existing State-of-the-Art Technologies

While deep learning models such as LSTM, GRU, and transformer-based architectures like BERT currently set benchmarks in sentiment analysis, they require substantial computational resources and large labeled datasets. In contrast, the PSO-optimized traditional classifiers used in this project offer a strong balance between performance and computational efficiency, making them suitable for applications with limited resources or where model interpretability is important. Although state-of-the-art deep learning models may achieve marginally higher accuracy, the integration of PSO for feature selection and parameter tuning provides a practical and scalable alternative, especially for medium-sized and resource-constrained projects. Furthermore, PSO can be incorporated into neural network pipelines for further optimization, suggesting its continued relevance in advanced sentiment analysis systems.

* 1. Future Directions

Future work should address the persistent challenge of class imbalance, particularly for the neutral sentiment class. Techniques such as oversampling, undersampling, or synthetic data generation (e.g., SMOTE) could improve generalization for underrepresented classes. Leveraging advanced feature extraction methods, including pre-trained language models like BERT or Word2Vec, may further enhance semantic understanding and classification performance. Exploring deep learning architectures, such as LSTMs or transformers, and integrating PSO for end-to-end optimization could yield even better results. Hyperparameter tuning through grid search, Bayesian optimization, or PSO itself will be essential for maximizing model performance. Implementing explainable AI (XAI) techniques will also enhance the interpretability of predictions, increasing trust and usability in real-world applications. Practically, the improved sentiment analysis system can support more accurate monitoring of public opinion, brand reputation management, and decision-making for businesses and policymakers, demonstrating broad applicability and value for future research and industry deployment.

**Appendix**

If there is material that should be in the project report but which would break up the flow or bore the reader unbearably, include it as an appendix. Some things which are typically included in appendices are: important and original computer programs, data files that are too large to be represented simply in the results chapters, pictures or diagrams of results which are not important enough to keep in the main text. Thus in the appendix, one may include

1. All data used in the report
2. Reference data/materials not easily available
3. Tables (where more than 1-2 pages)
4. Calculations (where more than 1-2 pages)
5. All key articles
6. List of all additional resource materials
7. List of equipment used for an experiment or details of complicated procedures.
8. In case of more than one appendix , they should be numbered as **Appendix A, Appendix B etc**

**Listings of the developed computer software should be given in an appendix. However, if the code is longer than 300 lines the listing should be given in a separate CD following proper indentation and comments.**

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