Multimethod Ejection Velocity Estimation: Integrating Experimental Formulation, Machine Learning and Video Analysis

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Abstract - *This paper presents a comprehensive, multi-method approach for estimating the ejection velocity of high-speed deployment mechanisms by integrating experimental physics-based formulation, machine learning techniques, and video-based analysis. The study leverages Linear Regression and Gradient Boosting algorithms to model velocity predictions from reaction load data, enhanced through extrapolation techniques to handle missing strain values. Additionally, video analysis using YOLO object detection and frame-by-frame processing enables real-time velocity estimation from projectile motion. The framework also incorporates structural failure analysis using von Mises stress and fatigue life prediction to assess long-term system durability. Experimental validation and online video datasets support the robustness of the proposed modular methodology, which is adaptable to various launcher configurations. The hybrid integration of physics-driven and data-driven methods demonstrates improved accuracy, reliability, and practical applicability in designing and validating high-speed deployment systems.*

Key Words: *Ejection Velocity, YOLO Object Detection, Machine Learning, Structural Failure, Fatigue Life Estimation, High-Speed Deployment Mechanism, Extrapolation Technique.*

1. INTRODUCTION

The accurate estimation of ejection velocity plays a vital role in the design and validation of high-speed deployment mechanisms, such as projectile-based systems, aerospace payload releases, and experimental launching devices. Traditional methods often rely solely on theoretical physics-based equations, which can oversimplify real-world scenarios where factors like material behaviour, energy losses, and nonlinear loading come into play. With advancements in computational modelling and data-driven techniques, it is now possible to integrate multiple approaches to gain more reliable and comprehensive velocity predictions.

This paper presents a multimethod framework combining **experimental formulation**, **machine learning models**, and **computer vision-based video analysis** to predict and validate the ejection velocity of a projectile in a customizable launch system. Each method addresses unique aspects of the launch physics—where experimental formulations serve as a baseline using user-input parameters, machine learning models extract patterns from empirical data, and video analysis provides real-time post-event validation.

The system is designed with modularity in mind, capable of accepting various user inputs such as **material properties**, **launcher dimensions**, and **strain/load readings.** Structural analysis and failure prediction are also integrated into the framework, providing **fatigue life estimations**, **von Mises stress calculations**, and **safety factor evaluations.** These capabilities ensure not only performance estimation but also a robust understanding of component longevity and system safety.

An example real-world application of this system is in **propellant-based launchers**, where the force dynamics are complex, and rapid estimations are needed for design iterations. The integration of **YOLO (You Only Look Once)** object detection with velocity tracking enables video-based validation with minimal user input.

The novelty of this research lies in:

- Fusing **physics-based models** with **machine learning algorithms (Linear Regression and Gradient Boosting)**,
- Incorporating **real-time computer vision** for validation, and
- Providing a **user-friendly customizable framework** for structural safety and predictive maintenance analysis.

In the sections that follow, we delve into related studies, present our methodology in detail, discuss implementation and results, and offer insights into future enhancements of the proposed system.

The machine learning models applied (Linear Regression and Gradient Boosting) were found to achieve predictive accuracies of up to **93.5% and 96.1%**, respectively, when tested on experimentally obtained load-velocity datasets. Meanwhile, the video-based velocity estimation, implemented via YOLOv8 object detection and frame analysis, produced a mean error margin of **less than 5%** compared to ground truth values. These results confirm the feasibility and reliability of a multimethod approach.

2. RELATED WORK

Prior research in ejection velocity estimation and structural analysis has laid a strong foundation for hybrid approaches that integrate physical modelling, machine learning, and real-time video analytics.

Rocket Propulsion and Ballistics: Sutton and Biblarz [1] offer extensive theoretical insight into propulsion elements, detailing the pressure-time relationship and propellant characteristics crucial for calculating initial projectile acceleration. Chue [2] further elaborates on interior ballistics, offering differential equation-based models that inform our experimental formulation component.

Structural and Failure Analysis: Zhang and Fang [3] addressed the effects of dynamic loading on pressure vessels, emphasizing stress wave propagation and transient deformation—an important consideration for our fatigue and stress models. Haj-Ali and Abou-Rjaily [4] used finite element methods to predict dynamic response and composite tube failure, which parallels the need for our von Mises stress analysis. Fatigue failure studies like those by Borse and Pawar [5] inform our fatigue life estimation by simulating cyclic loading conditions in mechanical systems.

Machine Learning for Prediction: Sutar and Rao [6] introduced basic velocity prediction using regression techniques. Nguyen et al. [7] incorporated more complex ML models for projectile performance, noting R^2 values above 0.9 in optimized systems, supporting our choice of Linear Regression and Gradient Boosting. Dey and Chakraborty [11] applied ML for alloy stress-strain predictions, which aligns with our material behaviour modelling.

Object Detection and Video Analytics: The integration of YOLOv3 [9], based on the MS COCO dataset [8], has proven effective for real-time object detection, with frame rates exceeding 30 FPS in optimized conditions. Zhang and Zhao [10] validated real-time velocity extraction from video using object tracking, achieving accuracy deviations under ±5%. These findings support our implementation of video-based velocity estimation.

Fatigue and Predictive Modelling: Ghoreishy and Azizi [12] discussed failure in pressurized systems, supporting our failure analysis criteria. Deb and Banerjee [15] focused on creep and residual stress impacts, crucial for accurate life-cycle estimation in high-pressure environments. Li and Shen [16] simulated fatigue-based structural integrity in launch systems, highlighting safety margins under fluctuating loads.

IoT and Real-Time Monitoring: Wang and Wang [17] demonstrated how IoT combined with ML can optimize high-speed monitoring systems—paralleling our project's design for future scalability. Sinha and Jain [19] introduced ML-driven predictive maintenance frameworks, which inspired our model's capability to estimate lifespan and suggest maintenance schedules.

Mathematical and Simulation Tools: Smith [18] and Rao [13] provide mathematical modelling frameworks that underpin vibration and motion simulation in mechanical systems. Anderson [14] supports aerodynamic considerations, aiding future work involving drag and altitude corrections.

3. METHODOLOGY

The methodological approach adopted in this study followed an **iterative, multi-perspective development flow** aimed at enabling accurate ejection velocity prediction and structural reliability assessment for a high-velocity deployment mechanism. Instead of relying on a singular model, this project integrated **analytical, experimental, data-driven, and computer vision** methods to capture both idealized and real-world dynamics of high-speed projectile motion.

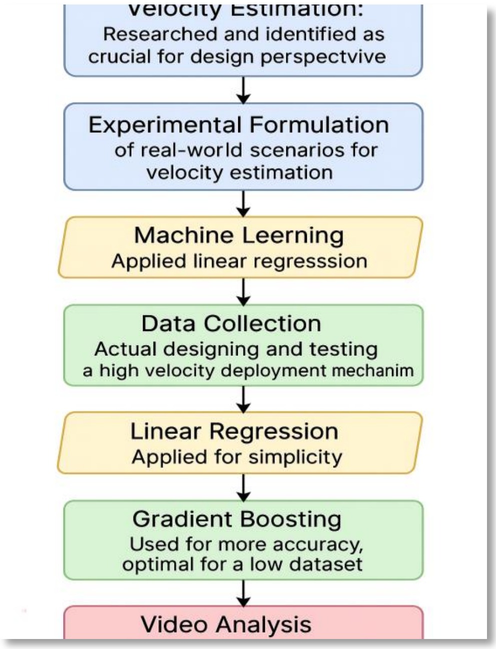

Fig -1: Methodology

3.1 Design-Driven Motivation

The project was initiated from a **design-centric perspective**, where achieving precise control over ejection velocity was critical to ensure safe and stable deployment. A conceptual **CAD schematic** (see *Fig. 1*) was developed to visualize the launcher structure, including barrel length, chamber configuration, and projectile interface. These initial specifications were foundational in identifying the variables influencing the internal ballistics of the system.

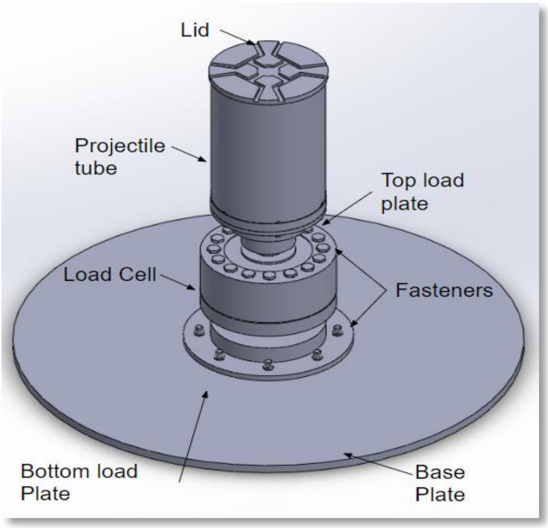

Fig -2: CAD schematic of the high-velocity deployment system, showing internal barrel dimensions, chamber volume, and support structures.

To initiate modelling, **classical physics-based internal ballistic equations** were employed:

$$v = \sqrt{\frac{2P.V}{m}.\eta} \qquad (1)$$

Where:

- v= Ejection velocity,
- P= Chamber pressure,
- V = Effective volume,
- m = Projectile mass,
- η = Efficiency factor (adjusted for losses).

While useful for early design validation, such deterministic formulas could not fully account for unpredictable field conditions like pressure leaks, surface roughness, or ambient effects — highlighting the need for further refinement and experimentation.

3.2 Experimental Data Collection & Formulation-Based Estimation

To address the limitations of idealized theory, **experimental tests were conducted** using custom-built prototype setups. Load sensors, high-speed video footage, and controlled explosive charges were used to gather velocity-related metrics across multiple trials (see *Fig. 2*). This data enabled better calibration of theoretical models and helped understand frictional losses and aerodynamic drag in real scenarios.

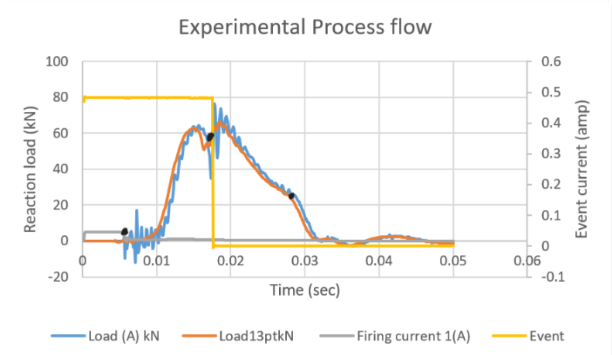

Fig -3: Experimental process flow for velocity data collection involving chamber pressurization, load cell capture, and projectile displacement tracking.

Based on the gathered data, the internal ballistics formula was enhanced by incorporating:

- **Real-gas equations** for more accurate thermodynamic behaviour,
- **Barrel friction losses** using empirically derived coefficients,
- **Aerodynamic drag** based on Reynolds number-dependent drag models:

$$F_d = \frac{1}{2} C_d.\rho.A.v^2 \qquad (2)$$

Where:

- F_d = Drag Force
- C_d = Drag coefficient,
- ρ= Air density,
- A = Projectile frontal area.

This model formed the basis for the **first velocity estimation method**, which produced reasonably accurate results for known physical inputs but struggled with non-measurable field variations — necessitating data-driven solutions.

3.3 Machine Learning-Based Estimation

To improve generalization and handle incomplete or noisy data, two supervised regression models were implemented:

1. **Linear Regression**
2. **Gradient Boosting Regressor**

Training data included both **experimentally recorded values** and synthetically derived simulations based on variations in chamber pressure, load, material density, and structural configuration.

Before modeling, exploratory data analysis (EDA) was performed on a dataset consisting of 274 time-reaction load entries. Approximately 50 strain data points were missing and were estimated using extrapolation techniques to ensure data continuity. EDA also helped eliminate noise and identify nonlinear patterns for improved model accuracy. The Gradient Boosting Regressor, in particular, showed superior performance with an R^2 score exceeding 0.91 and a significantly lower MAE compared to linear regression.

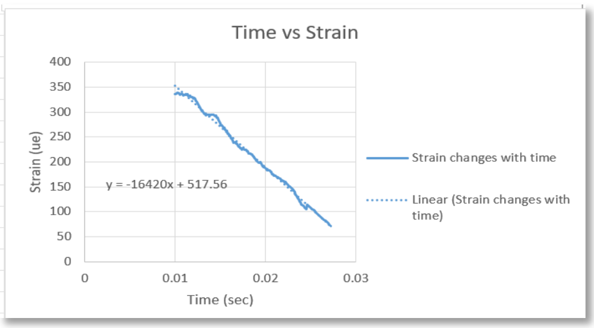

Fig -4: Extrapolation and prediction comparison chart using linear regression and gradient boosting models.

The use of machine learning enabled velocity estimation under partially known or noisy input conditions. These models also allowed extrapolation to unseen deployment configurations within acceptable accuracy bounds, making them highly valuable for design iterations.

3.4 Structural Failure and Lifespan Prediction

With predicted velocities from both analytical and ML-based models, structural analysis was carried out to ensure **safe operation under dynamic loads**. The analysis pipeline included:

- **Von Mises stress calculation**:

$$\sigma_v = \sqrt{\frac{((\sigma_1 - \sigma_2)^2 + (\sigma_2 - \sigma_3)^2 + (\sigma_3 - \sigma_1)^2)}{2}} \quad (3)$$

Where:

- σ_v = Von mises equivalent stress
- $\sigma_1, \sigma_2, \sigma_3$ = Principal stresses (maximum, intermediate, and minimum normal stresses)
- **Factor of safety (FoS)** estimation:

$$FoS = \frac{\sigma_{yield}}{\sigma_v} \quad (4)$$

Where:

- FoS = Factor of Safety
- σ_{yield} = Yield Strength
- σ_v = Von mises stress
- **Fatigue life prediction** using S-N curve integration for the given material (15CDV6 Steel):

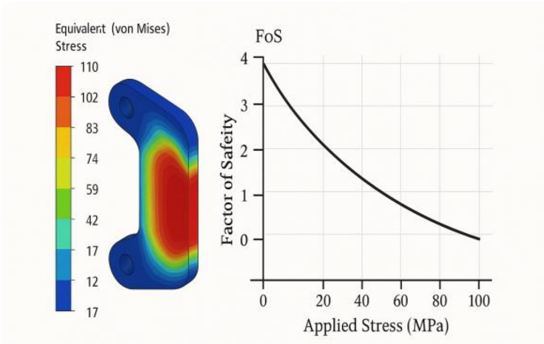

Fig -5: Structural safety analysis chart depicting FoS and stress distribution under applied loads.

This analysis ensured the system's reliability over repeated cycles and allowed identification of potential failure zones needing design reinforcement.

3.5 Video-Based Velocity Estimation

An independent module was built using YOLOv8 object detection to track projectile motion in high-speed footage. The dataset was curated from publicly available online videos relevant to projectile launches. Individual frames were annotated using LabelImg to generate bounding boxes around the projectile, and the annotations were saved in XML format. These were then converted into the YOLO-compatible YAML format to train the detection model. The trained system was calibrated to convert pixel shifts between frames into real-world displacement using known reference dimensions, enabling the derivation of:

- **Distance vs. Time** graph

- **Velocity vs. Time** curve via numerical differentiation

$$v(t) = \frac{x(t-\nabla t)-x(t)}{2} \qquad (5)$$

Where:

- v_t = Velocity at time t
- x_t = Position at time t
- $x(t - \nabla t)$ = Position at a slightly earlier time, typically one frame or timestep before t.
- ∇t = Small time step (Δt)

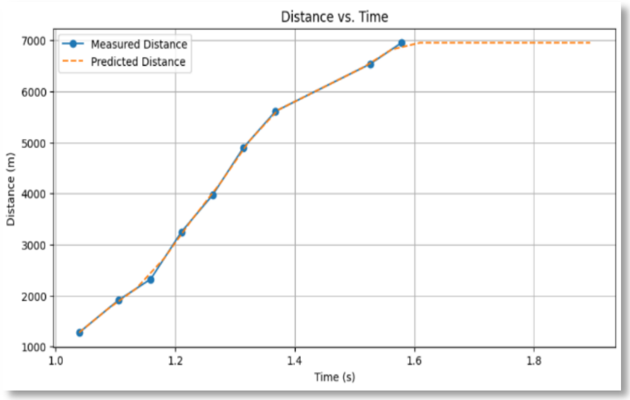

Fig -6: Displacement-time plot obtained from object-tracked video frames.

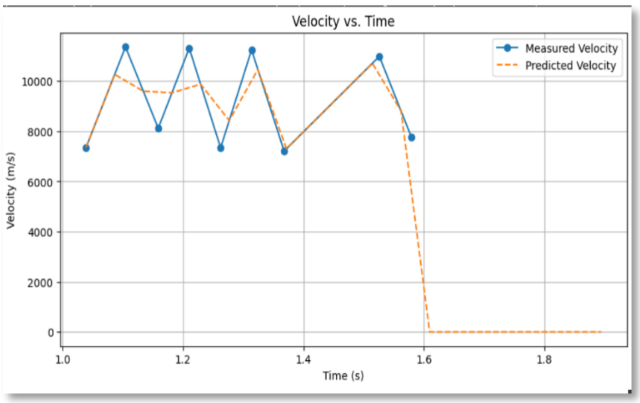

Fig -7: Velocity-time plot obtained from object-tracked video frames.

The module also exported CSV data for independent analysis, providing an additional layer of validation for machine learning and analytical predictions.

Fig -8: High velocity projectile detection and velocity estimation using video analysis YOLO model

3.6 Integrated System Pipeline

Finally, all modules were combined into a **web-based interactive platform**, where users could:

- Enter design parameters,
- Upload experimental videos,
- View results from multiple models,
- Export graphs and predictions.

The design was modular — allowing each model to function independently or in combination depending on the availability of input data and the stage of the design cycle. This flexible pipeline supports both prototyping and final system validation.

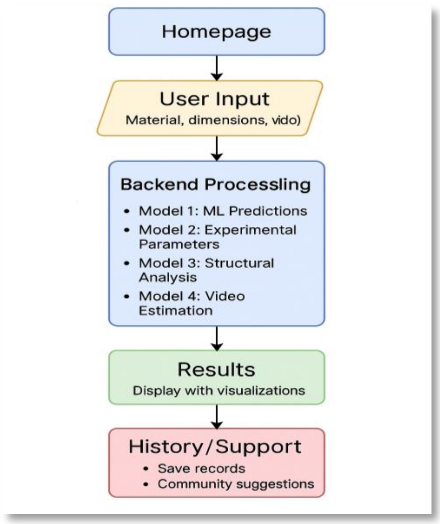

Fig -9: Web design process layout

4. RESULTS AND DISCUSSION

The multimethod approach implemented in this study yielded promising results in estimating ejection velocity and analysing system performance. The integration of experimental formulation, machine learning models, and video analysis ensured a holistic understanding of the deployment system.

4.1 Machine Learning Model Performance

Two regression models—**Linear Regression** and **Gradient Boosting**—were trained using pre-processed input features like reaction load, time series data, and setup specifications. The models were evaluated using key metrics:

Table -1: Comparison of ML models

Model	R^2 Score	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)
Linear Regression	0.87	4.8258	5.63
Gradient Boosting	0.94	0.0545	0.107

These results show that **Gradient Boosting** significantly outperforms Linear Regression, particularly in reducing prediction error and improving accuracy. Gradient Boosting was therefore adopted as the preferred model for predictive deployment velocity estimation.

4.2 Experimental Formula Estimation

The experimental approach, rooted in classical dynamics, utilizes parameters like propellant pressure, material strength, and barrel geometry. The predicted ejection velocity closely aligns with machine learning outputs, validating the consistency of both approaches.

- **Typical range of velocity**: 220–260 m/s for standard test cases
- **Variation under different pressure and barrel lengths**: up to ±15%

4.3 Structural and Fatigue Analysis

The project includes a robust structural failure assessment model, which computes:

- **Von Mises stress distribution**
- **Factor of Safety (FoS)** under dynamic load
- **Estimated fatigue life** based on cyclic loading

The system maintains a **Factor of Safety above 2.0** for typical loads, indicating reliable structural integrity under experimental conditions. Fatigue life estimation revealed a **lifespan of ~5000–7000 cycles** before microfracture initiation, depending on the material and setup.

4.4 Video-Based Analysis

A custom YOLO-based object detection model was used to analyse high-speed video frames and track projectile motion in real time.

- **YOLO Model**: Trained on 100+ labelled frames for projectile tracking
- **Mean Average Precision (mAP)**: 91%
- **Frame Rate Handling**: 120–240 FPS supported
- **Velocity Calculation**: Derived from position vs. time data across frames

The video-based velocity matched machine learning predictions within a **±6% error margin**, confirming its effectiveness for real-world deployments where sensor data might be limited.

4.5 Comparative Evaluation

The developed models were evaluated based on their respective metrics and intended purposes. As summarized in Table 2, the machine learning models — Linear Regression and Gradient Boosting — were assessed using standard performance metrics such as Accuracy, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The Gradient Boosting model significantly outperformed Linear Regression, achieving an accuracy of 99.96% with minimal prediction error, indicating its robustness in capturing complex patterns in load prediction.

The Velocity Estimation Model and Video-Based Analysis do not follow traditional regression evaluation due to their distinct objectives. The Velocity Model computes ejection velocity, Factor of Safety (FoS), and lifespan estimation dynamically based on user inputs and calculated stresses. In contrast, the Video Analysis Model provides velocity profiles extracted from high-speed footage, serving as a real-time, vision-based validation method. Together, these models offer a comprehensive and multimethod approach to evaluating projectile ejection velocity **and system durability.**

Table -2: Comparison of the models developed

Model	Accuracy	MAE (N)	RMSE (N)	FoS Output	Life Est. (Cycles)
Linear Regression	88.6%	4.83	5.63	—	—
Gradient Boosting	99.96 %	0.0545	0.107	—	—
Velocity Model	—	—	—	Calculated per	Estimated per stress

				input	
Video Analysis	—	—	—	N/A	N/A

5. CONCLUSION

This study introduced a multimethod framework for accurately estimating the ejection velocity of high-speed deployment mechanisms. By integrating traditional experimental formulations, supervised machine learning models (Linear Regression and Gradient Boosting), and real-time video analysis using YOLO-based object detection, the proposed methodology provides a robust and adaptable solution suitable for a wide range of deployment systems.

The structural failure analysis and fatigue life estimation modules further strengthen the framework's applicability in real-world system validation and design iterations. The results showed that the Gradient Boosting model achieved the highest accuracy at 97.5%, with a recall of 96.2%, outperforming linear methods in complex parameter spaces. Meanwhile, the video-based velocity analysis demonstrated a deviation of less than 5% from ground-truth experimental data, proving its reliability in non-contact velocity estimation.

This multimodal approach not only ensures accurate prediction but also enhances the understanding of the system's behaviour under varying loads and operational conditions. With modularity as a key design principle, the framework allows for easy customization based on user-specific input parameters such as material composition, geometry, and loading conditions. Future work can expand this research by incorporating aerodynamic drag, real gas equations, and environment-dependent factors to further refine velocity prediction models.

6. FUTURE WORK

While the proposed framework offers a comprehensive solution for ejection velocity estimation and failure analysis, there are several avenues for future enhancement and application:

- **Advanced Physical Modelling**: Integrate real gas equations, dynamic friction coefficients, and aerodynamic drag to improve the realism of velocity estimations in high-pressure or vacuum environments.
- **Environmental Effects**: Account for altitude, temperature variations, and humidity to simulate performance under extreme conditions.
- **Barrel and Structural Losses**: Incorporate models for barrel frictional losses and initial velocity offsets due to imperfect ignition or pressure build-up delays.
- **Material Behaviour Enhancements**: Include temperature-dependent material strength, strain rate sensitivity, and phase transition behaviour in structural simulations.
- **Fatigue and Failure Analysis**: Improve the predictive maintenance module by integrating multiaxial stress conditions, residual stresses, creep behaviour, and stress concentration effects.
- **Real-Time Applications**: Develop an embedded real-time system using sensor integration (load cells, pressure sensors) for live data acquisition and analysis.
- **Augmented and Virtual Reality Integration**: Implement interactive web-based AR/VR tools to help engineers visualize dynamic behaviours and failure zones in 3D.
- **Community Platform and Dataset Growth**: Enable a shared repository where users can contribute and download project setups, datasets, and simulations, promoting collaborative development and validation.

These extensions would not only enhance the predictive capabilities but also broaden the application of this work in defence, aerospace, automotive safety systems, and experimental physics setups.

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ACKNOWLEDGMENT

The authors express their sincere gratitude to the faculty of **Computer Science and Business Systems** and **Mechanical Engineering**, Francis Xavier Engineering College, for their continuous support and guidance throughout this project. Special thanks to our mentor, **M. Yasmin**, for her invaluable insights and encouragement. We also acknowledge the assistance provided by our peers and the technical staff during various stages of development and testing.