RESEARCH



Predicting Engagement And Boredom in Online Video Lectures Shreyash Patil, Anushka Engavle, Rugved Langhi Department of Information Technology, The Bombay Salesian Society's Don Bosco Institute of Technology, Mumbai - 400070

ABSTRACT

Our study utilizes datasets from Daisee and Kaggle A diverse range of studies explores methods for

BACKGROUND INFORMATION

to forecast student interest and boredom in online assessing student engagement in online learning, lectures. We employ CNN for image feature ex-lemploying techniques like facial behavior analysis, traction and LSTM for sequential data analysis from sentiment analysis from images[1], and deep video frames. By comparing these techniques across learning approaches[2]. These studies utilize various three datasets, we provide insights into their effec- datasets and models, including LSTM and CNN[2], tiveness in predicting engagement. Our findings to predict engagement levels and analyze facial offer practical guidance for educators to enhance expressions. Insisghts from these studies highlight the online teaching strategies, fostering greater complexity of assessing engagement and offer practistudent engagement and reducing boredom. We calimplications for educators to enhance online teachfound that CNN was better for all the three dataset. Ing strategies and improve learning experiences[3].

RESUITS

| | | Dataset 1(St | udent Engagem | ent from kaggle |) | | | Dataset 1 | (Student Engag | ement fron | n kaggle) | | | | | |
|------------|-----------------------|-----------------|---------------|-----------------|-----|-----|------------|-----------------------|-----------------|------------|-----------|-----|-----|--|--|--|
| Attributes | actual value | predicted value | TP | TN | FP | FN | Attributes | actual value | predicted value | TP | TN | FP | FN | | | |
| engagement | 848 | 109 | 109 | 581 | 0 | 739 | engagement | 69 | 69 | 69 | 352 | 0 | 0 | | | |
| boredom | 556 | 1283 | 556 | 873 | 727 | 0 | boredom | 71 | 52 | 52 | 350 | 0 | 19 | | | |
| confusion | 11 | 0 | 0 | 1418 | 0 | 11 | confusion | 73 | 73 | 73 | 348 | 0 | 0 | | | |
| frustrated | 14 | 0 | 0 | 1415 | 0 | 14 | frustrated | 72 | 77 | 72 | 349 | 5 | 0 | | | |
| look away | 0 | 37 | 0 | 1429 | 37 | 0 | look away | 84 | 85 | 84 | 337 | 1 | 0 | | | |
| drowsy | 0 | 0 | 0 | 1429 | 0 | 0 | drowsy | 52 | 65 | 52 | 369 | 13 | 0 | | | |
| Total | 1429 | 1429 | | | | | Total | 421 | 421 | | | | | | | |
| | Dataset 2(DAISEE) | | | | | | | Dataset 2(DAISEE) | | | | | | | | |
| Attributes | actual value | predicted value | TP | TN | FP | FN | Attributes | actual value | predicted value | TP | TN | FP | FN | | | |
| engagement | 848 | 1429 | 848 | 581 | 581 | 0 | engagement | 1674 | 1711 | 1674 | 110 | 37 | 0 | | | |
| boredom | 556 | 0 | 0 | 873 | 0 | 556 | boredom | 75 | 48 | 48 | 1709 | 0 | 27 | | | |
| confusion | 11 | 0 | 0 | 1418 | 0 | 11 | confusion | 18 | 25 | 18 | 1766 | 7 | 0 | | | |
| frustrated | 14 | 0 | 0 | 1415 | 0 | 14 | frustrated | 17 | 0 | 0 | 1767 | 0 | 17 | | | |
| Total | 1429 | 1429 | | | | | Total | 1784 | 1784 | | | | | | | |
| | Dataset 1 + Dataset 2 | | | | | | | Dataset 1 + Dataset 2 | | | | | | | | |
| Attributes | actual value | predicted value | TP | TN | FP | FN | Attributes | actual value | predicted value | TP | TN | FP | FN | | | |
| engagement | 873 | 1429 | 873 | 556 | 556 | 0 | engagement | 1674 | 1403 | 1403 | 110 | 0 | 271 | | | |
| boredom | 556 | 0 | 0 | 873 | 0 | 556 | boredom | 110 | 381 | 110 | 1674 | 271 | 0 | | | |
| Total | 1429 | 1429 | | | | | Total | 1784 | 1784 | | | | | | | |
| | Fig. 2 LSTM Result | | | | | | | Fig. 3 CNN Result | | | | | | | | |

Fig. 2 LSTM Result

| Madal | Accuracy | | | | | | | |
|-------|-----------|-----------|---------------|--|--|--|--|--|
| Model | Dataset 1 | Dataset 2 | Mixed Dataset | | | | | |
| CNN | 0.985 | 0.988 | 0.858 | | | | | |
| LSTM | 0.871 | 0.5045 | 0.463 | | | | | |

Fig. 4 Accuracy Table

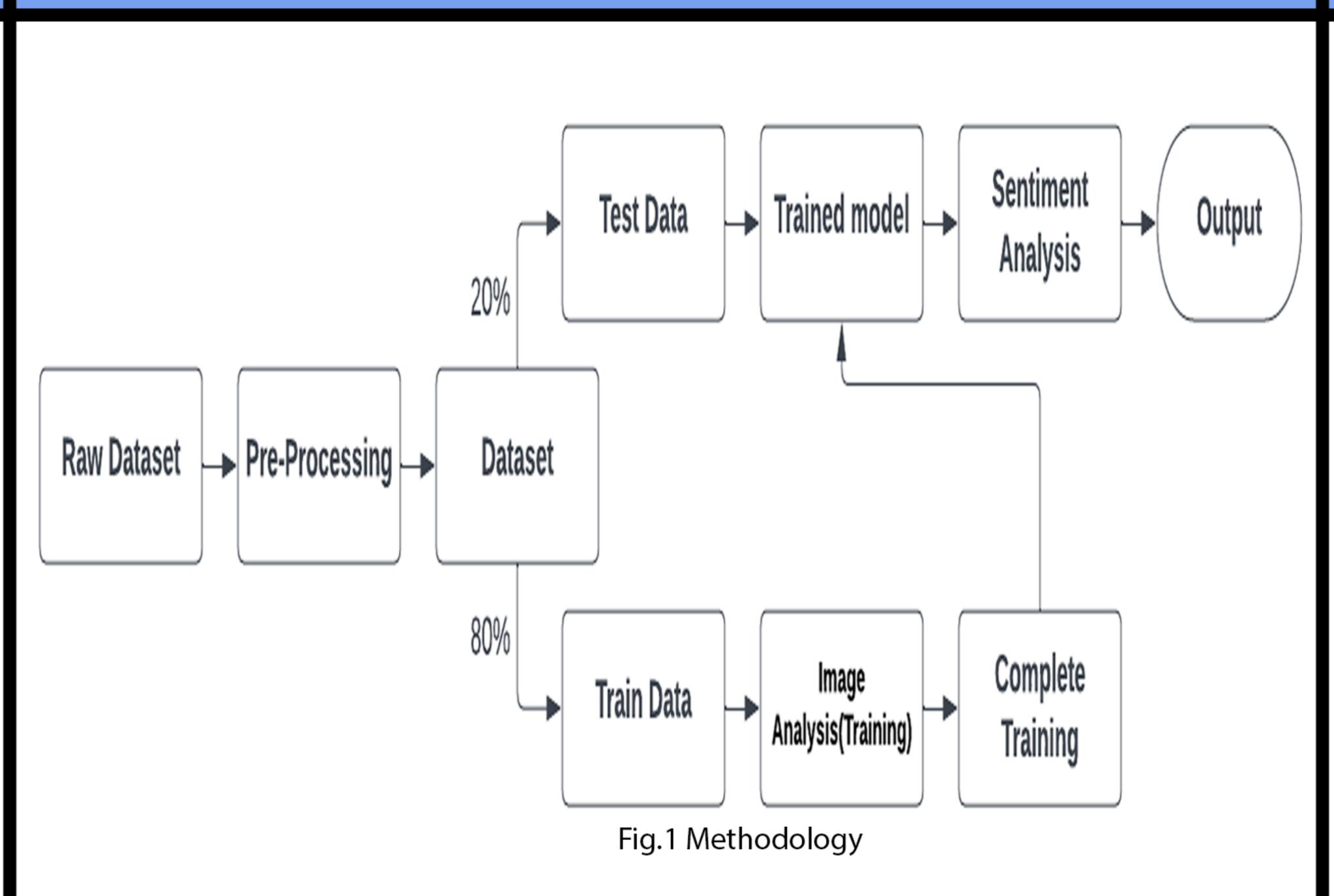


Fig. 5 Output

INTRODUCTION

The lack of reliable tools for assessing student engagement in virtual classes prompts the need for a Video Analyzer for Student Engagement. Our project aims to address this gap by developing an automated system that objectively boredom during and engagement lectures. With a focus on real-time feedback and video techniques, analysis advanced valuable educators system insights tailor teaching methods learning outcomes in the enhance online evolving landscape

METHODOLOGY DESIGN



CONCLUSION

Our project sheds light on leveraging [1]J. machine learning and computer vision for engagement in online predicting lectures. While Model 1 excelled across diverse datasets, Model 2 faced challenges, highlighting importance the understanding model adaptability. Moving forward our, insights pave the way for tailored teaching methods and improved virtual learning experiences, signalpotential ongoing education. innovation online

REFERENCES

A.Johnson.(2022)."A Ensemble-Based Face Expression Recognition Approach for Image Sentiment Analysis." Multimedia Tools and Applications, 35(7), 1987-2001.

[2]N. Johnson, P.Anderson.(2017)."Analysis of Student Sentiment During Video Class with Multilayer Deep Learning Approach." 2017 IEEE Internation Conference on Cybernetics and Intelligence, 135-142. Computational

[3]C. SAntiago Jr., A.T. Alarcon, et al.(2020). "Sentiment Analysis of Students' Experiences During Online Learning in a State University in thr philippines." Eduction and Information 3971-3990. Technologies, 25(5),