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Crowd Trust: Evaluating the Integrity of Campaigns on Donation Based Crowdfunding Platforms

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***Abstract*—** The growing popularity of online crowdfunding platforms has also brought into question the credibility of these platforms. Millions of campaigns are posted on these websites each year, and while the principle of donating remains philanthropic, the increase in false campaigns being added to mislead the public has been rampant. Although most crowdfunding platforms offer verifications for the hosted campaigns, multiple fraudulent campaigns still go undetected. These campaigns may seem legitimate, but there are certain factors and minute details that differentiate them from genuine campaigns. Various methods to identify the genuinely of these campaigns might exist, but most of them do not consider a well-rounded set of features. In this paper, we propose Crowd Trust, a fraud detection mechanism that focuses on donation-based crowdfunding campaigns. Crowd Trust leverages both textual and non-textual attributes using advanced Natural Language Processing (NLP) techniques, along with a pre-trained Distil BERT model to analyze and categorize campaigns based on their credibility.

***Keywords*—** *Crowdfunding Fraud Detection; Sentiment Analysis; Anomaly Detection; Text Classification; Credibility Analysis; Natural Language Processing (NLP); Distil BERT*

I. INTRODUCTION

Crowdfunding is a unique way of fundraising, allowing individuals and/or organizations to finance a cause, charity, or even a business. It draws its inspiration from ideas such as crowdsourcing and microfinance but is different from them as it leverages the efficiency of the Internet to connect donors and recipients. By overcoming traditional funding barriers, crowdfunding has been labeled as a revolutionary solution to empower people through financial contributions.

Crowdfunding can be widely classified into four main categories:

1. Donation - Based Crowdfunding
2. Rewards - Based Crowdfunding
3. Equity - Based Crowdfunding
4. Debt - Based Crowdfunding

Popular crowdfunding platforms (CFPs) including GoFundMe, Kickstarter, and Indiegogo have all played a pivotal role in the rise of the global crowdfunding market, which achieved a valuation of $12.27 billion in 2021. The market currently spans across 171 countries, showcasing how the industry has emerged as a significant and evolving force. With a Compound Annual Growth Rate (CAGR) of 11%, the crowdfunding market is projected to grow twice as large by 2027 [1].

However, as the industry grows both in size and popularity, there has been a significant rise in the presence of deceptive activity on crowdfunding platforms. Campaign organizers appeal to the generosity of donors, and on several occasions, mislead donors due to a lack of transparency, or through manipulation of campaign information.

This study aims to put forward analyses on aspects of misleading campaigns on donation-based CFPs, and how these aspects are used to build a machine learning model capable of identifying fraudulent and misleading campaigns.

In this research study, we investigate campaigns primarily from the donation-based site GoFundMe, the largest crowdfunding website in the world [2].

With an overall 80 percent control in the social crowdfunding market [2][3], GoFundMe's prominence and scale make it a perfect platform to analyze patterns of both legitimate and fraudulent campaigns.

To add on to the data we collect from GoFundMe, we also gather confirmed cases of fraudulent campaigns from GoFundMe [4] and Reddit [5].

Approximately 20,000 campaigns are collected from all sources, and this data is preprocessed to give us a dataset consisting of textual and non-textual features of both fraudulent and legitimate campaigns. This dataset consists of textual features from each campaign such as-

- campaign category
- campaign title
- campaign description
- campaign organizer and beneficiary alongside non-textual features -
- number of donations
- comment count
- update count
- amount required and amount collected.

By analyzing the patterns from these features, we implement Distil BERT as part of a larger machine learning model, which generates a numerical score that gives us an estimation of the likelihood of a particular campaign being legitimate or fraudulent.

II. RELATED WORK

In his work, Mollick [6], lays down the foundation of an analysis on the successes and failures of crowdfunding, by exploring Kickstarter, a rewards-based CFP. The author suggests that a campaign's success is linked to higher project quality and how well the organizer is connected to people through social media networks.

Kemang and Gosal [7] elaborated on the factors that affect donation intention on donation-based platforms by incorporating the theories of behavioral sciences - namely the Theory of Planned Behavior, Social Presence Theory and S-O-R Theory. Their study helps us in establishing the framework for our model to identify patterns within campaigns hosted on CFPs, by highlighting the role of perceived credibility in donation intention.

Perez et al. embraced a technical approach in their study [8], by making use of a combination of machine learning models, to analyze textual and visual attributes from over 700 campaigns collected from multiple donation-based CFPs. Their approach involved extraction of textual features through a combination of sentiment analysis and Named-Entity Recognition (NER) [9] , along with emotion recognition and object recognition to extract visual cues from images posted on campaigns. The study was successful in coming up with a model that accurately predicted the likelihood of a campaign being fraudulent by leveraging the above-mentioned features to come up with a robust solution for fraud detection.

Other research works have dealt with similar detection of fraud and misleading activity, but they focus on different domains such as credit card fraud detection [10] and peer-to-peer lending fraud detection [11].

III. A Background on Donation-Based Cfps, Fraud and Gofundme

A. Donation-Based Crowdfunding Platforms:

As discussed earlier, crowdfunding platforms (CFPs) are online platforms that connect potential donors with campaigns that support a particular cause. Donation-based CFPs support a more novel type of crowdfunding wherein donors donate to a cause of their liking, without expecting financial compensations in return. The rationale behind these platforms is to support humanitarian and artistic projects, to contribute to a philanthropic cause [12]. Well-known examples of donation-based CFPs include GoFundMe, Fundly, Fundrazr, Milaap, *et cetera*.

The appeal of such platforms is due to their large reach and efficiency. Their ability to connect donors and funding recipients, along with hassle-free payment options and great user experience, make these platforms a preferred choice amongst many individuals looking to support charitable causes [13].

B. Defining Fraud in Terms of Donation-Based Cfps:

Fraud can be defined as an intentional misrepresentation of a fact made by one actor to another, inducing the other to act upon it. [8] [14].

In the context of donation-based CFPs, fraud involves misleading, deceptive practices used by campaign organizers to manipulate and trick donors into contributing money for causes that are exaggerated or fabricated.

Fraudulent activities on crowdfunding platforms can be detected using indicators such as:

1. Linguistic indicators such as spelling and/or grammatical errors and less verifiable, objective information [15]
2. Campaign-specific indicators, including the level of detail in campaign descriptions, the background and social media activity of campaign creators, and campaign characteristics such as funding duration, all of which are significantly associated with the likelihood of detecting fraudulent crowdfunding projects [16]
3. Unusual activity related to donor behavior, such as a sudden uptick in donor contributions, excessive amounts of donations from anonymous donors, and other patterns that deflect from typical crowdfunding trajectories
4. Transparency indicators such as infrequent updates by the campaign organizer, no information about the beneficiary/recipient of the campaign funds, lack of evidence justifying the motive for the campaign
5. Emotional cues like heavily dramatic language and exaggerated appeals; manipulative language is a technique often used by fraudulent organizers to exploit donors' emotional vulnerability and turn their focus away from the lack of concrete evidence supporting the campaign's cause.

Our work focuses on identifying and analyzing these indicators to detect potentially misleading campaigns. By evaluating linguistic, campaign-specific transparency and emotional indicators, alongside donor behavior, our team aims to build an extensive model to detect fraud on donation-based CFPs.

C. An Overview of Gofundme:

Founded in 2010 [17], GoFundMe helped popularize the concept of donation-based crowdfunding for individuals or charitable organizations in need of help and monetary donations.

Spanning over 20 countries, GoFundMe has raised over $17 billion from more than 200 million contributions, as of 2022 [18]. The platform allows users to create personalized fundraising campaigns for a variety of causes, including medical expenses, disaster relief, education, and community support initiatives.

GoFundMe makes it simple for people to create campaigns and raise funds, while also ensuring donors feel confident in their contributions. Features like detailed campaign descriptions and regular updates allow donors to feel more connected to the cause. Campaign organizers can also use various social media tools to reach a wider audience and gain more support.

Over time, GoFundMe has established itself as the most popular donation-based CFP, providing an

accessible platform for individuals to create campaigns and secure financial support. By simplifying the process of fundraising and incorporating tools that enhance donor confidence—such as transparent updates and clear campaign goals—it has successfully built a reputation for reliability.

IV.Methodology

The methodology employed in this study for detecting fraudulent campaigns within donation-based crowdfunding platforms (CFPs) involves multiple stages, including data collection, preprocessing, sentiment analysis, and both textual and non-textual data analysis. These stages are crucial for developing an effective machine learning model capable of distinguishing fraudulent campaigns from legitimate ones.

A.Data Collection

Data for this study was sourced from multiple platforms to ensure a balanced dataset consisting of both fraudulent and non-fraudulent campaigns:

1. *GoFundMe*: Data from verified non-fraudulent campaigns were obtained from GoFundMe. These campaigns were sourced by scraping publicly available data and leveraging GoFundMe's internal verification mechanism to ensure authenticity.
2. *GoFraudMe:* A portion of the dataset was gathered from GoFraudMe, a platform dedicated to tracking fraudulent crowdfunding campaigns. This data provided confirmed cases of fraudulent campaigns across various platforms.
3. *Reddit:* Campaigns flagged as fraudulent by users on Reddit were also added to the dataset. Reddit's community-based 'subreddits' helped identify fraud cases that were not covered by GoFraudMe.
4. *GoFundMe Sitemap:* URLs of medical donation-based campaigns were scraped from the GoFundMe sitemap, which offers a structured view of available campaigns. This allowed for systematic extraction of campaign links. In total, around 20,000 URLs were collected from these sources.
5. *Data Preparation*: After collecting the URLs, a subset of the data was randomly shuffled and split into training and testing datasets. This ensured that both fraudulent and non-fraudulent campaigns were adequately represented in both subsets.

The dataset contains several key attributes that were considered during analysis:

- *Campaign category*: The type of the campaign (e.g., medical, education, disaster relief).
- *Campaign title*: The title of the campaign as described by the organizer.
- *Campaign description*: A detailed description of the campaign's purpose and funding goals.
- *Campaign organizer*: Information regarding the individual or entity organizing the campaign.
- *Campaign beneficiary*: The individual or group receiving the funds.
- *Amount required*: The total amount requested by the campaign organizer.
- *Number of donations*: The total count of donations received by the campaign.
- *Comment Count:* The number of comments listed in the campaign.
- *Update count*: The number of updates provided by the campaign organizer.

B.Data Preprocessing

Upon collection, the data was preprocessed to ensure its readiness for analysis:

1. *Data Cleaning*: Special characters and extraneous symbols were removed from both textual and numerical attributes to prevent any issues during analysis and model training.
2. *Handling Missing Data*: Any missing values in the dataset were filled with placeholders such as 0 for numerical data and "Information not found," "Anonymous," or "NIL" for textual data. This ensured that the model could process incomplete records without generating errors.
3. *Stopword Removal*: Common stopwords, such as "the," "is," and "and" were removed from the

campaign descriptions to allow for a more focused analysis of meaningful keywords.

C.Sentiment Analysis

Sentiment analysis was applied to campaign descriptions to further evaluate their likelihood of being fraudulent:

1. *Sentiment Detection Model:* The sentiment of each campaign description was analyzed using *DistilBERT*, a transformer-based language model. DistilBERT was chosen for its ability to process text efficiently while providing accurate sentiment classifications.
2. *Labeling:* Each campaign was assigned a sentiment label (fraud or non-fraud) based on the legitimacy of the campaign. This was achieved by fine-tuning the model to recognize sentiment patterns indicative of fraudulent campaigns.
3. *Confidence Scoring:* A percentage score indicating the likelihood of a campaign being fraudulent was generated based on the sentiment analysis, allowing for further refinement of the fraud detection process.

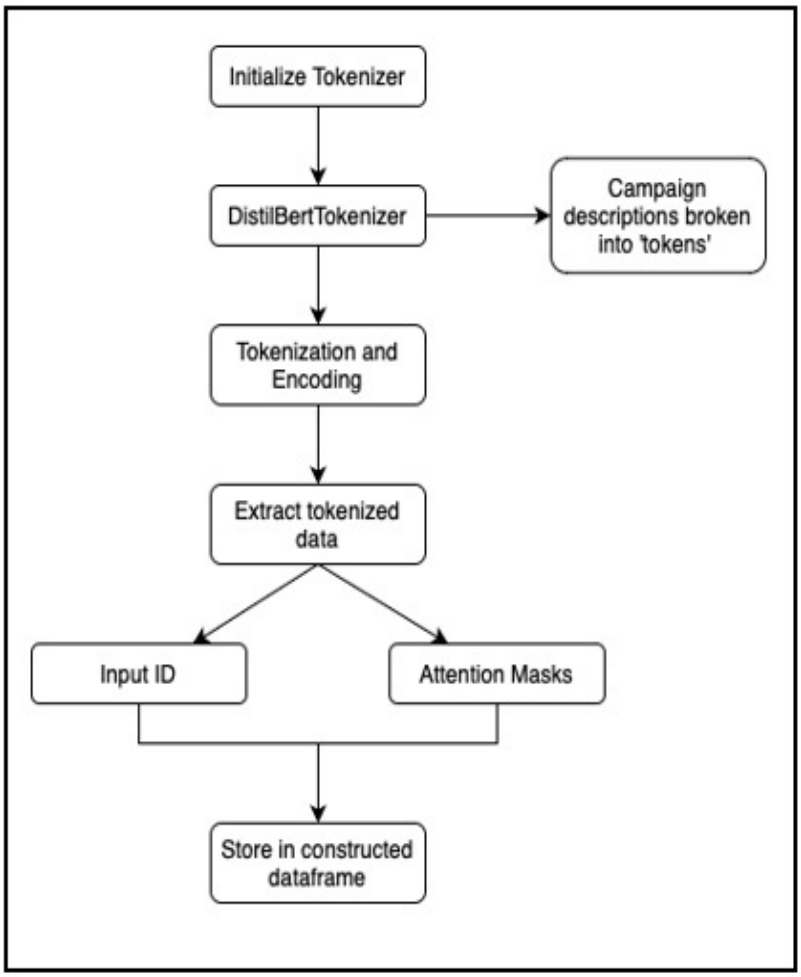

Fig. I. DistilBERT Working.

D.Textual Data Analysis

Additional analysis was performed on the textual attributes of the campaigns, particularly the campaign category and campaign description:

1. *Keyword Frequency Analysis:* The top ten most used keywords in each campaign category were identified with the help of Count Vectorizer. The campaign descriptions were then analyzed to

determine the frequency with which these keywords were utilized. Higher frequency of the keywords helped identify campaigns that were associated with a lower likelihood of fraud.

2. *Campaign Description Quality:* Campaigns with incomplete descriptions, placeholder text, or missing values were flagged as potentially fraudulent. A lack of detail or transparency in campaign descriptions is often indicative of fraudulent intent.
3. *Campaign Beneficiary:* This attribute was scrutinized, with campaigns that listed no beneficiary or an anonymous one being more likely to be fraudulent. Transparent information about the beneficiary is essential for establishing trust in crowdfunding campaigns.

E.Non-Textual Data Analysis

The analysis extended beyond textual data to include non-textual attributes such as Update Count:

1. *Update Count Threshold*: A range of update counts was plotted to identify a threshold, above which campaigns were classified as more likely to be legitimate. A lack of updates or inconsistent update frequency is often a sign of fraud.
2. *Placeholder and Missing Data:* Campaigns with missing values in non-textual columns or with placeholder text were flagged as suspicious. These campaigns often had a higher likelihood of being fraudulent, as they lacked transparency in key data fields.

F. Model Development

The dataset was split into training and testing sets using an 80:20 ratio, with the aim of training the model on a diverse range of examples while evaluating its performance on unseen data:

1. *Training the Model:* Various machine learning algorithms were tested, including Random Forest, to evaluate the campaigns based on the textual and non-textual features identified earlier. The model learned to classify campaigns as fraudulent or non-fraudulent based on these features.
2. *Feature Selection:* The importance of each feature was evaluated to understand which attributes (e.g., campaign description, update count) had the most significant impact on the model's predictions.

G.Model Evaluation

The model was evaluated using the following performance metrics:

- *Accuracy:* The percentage of correctly classified campaigns out of all predictions.
- *Precision:* The percentage of correctly predicted fraudulent campaigns among all predicted fraudulent campaigns.
- *Recall:* The percentage of correctly predicted fraudulent campaigns among all actual fraudulent campaigns.

A user interface was developed to allow users to check the likelihood of a campaign being fraudulent. Users could input the relevant campaign details, and the system would provide a prediction along with reasoning for the classification.

H.Results

Four factors were considered to evaluate the fraud likelihood score of each campaign:

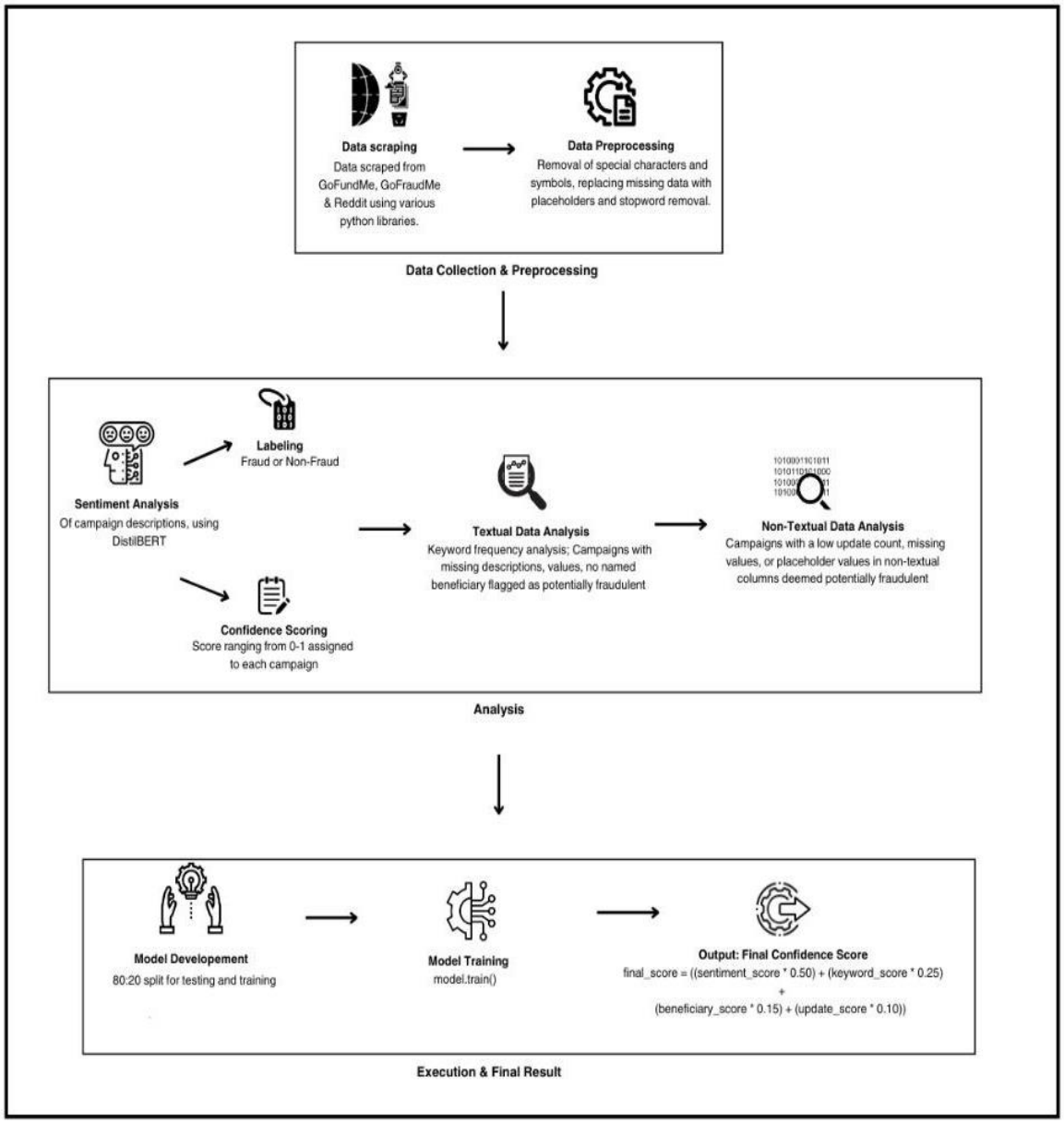

Fig. II. Methodology.

1. Sentiment of the campaign description
2. Frequency of category-based keywords in the campaign description
3. Update count of each campaign
4. Presence of a campaign beneficiary

These factors are primarily considered as they are the most consistently available across most of the campaigns. Additionally, these factors contribute most heavily to the integrity of the campaigns and indicate significant user involvement. Utilizing the factors above, our team developed a formula to calculate the fraud likelihood score of a campaign. Each factor was multiplied with a weighted value corresponding to its proposed ability to indicate fraud.

$$\textit{final score} = (\textit{(sentiment score} * 0.50) + (\textit{keyword score} * 0.25) + (\textit{beneficiary score} * 0.15) + (\textit{update score} * 0.10)) \quad (1)$$

Once the model processed a campaign, the final fraudulence score was calculated, users were given a conclusive review of the likelihood of that campaign being fraudulent. This review included the individual scores of the contributing factors, along with the final score calculated using the formula above. These

scores ranged between 0 and 1; a score close to 0 indicated a lower likelihood of fraudulence, while a score closer to 1 suggested a higher chance of the campaign being potentially fraudulent.

V.Conclusion

Our study presents a novel approach to identifying fraudulent campaigns on donation-based CFPs. By integrating the analysis of textual and non-textual features with the application of a trained DistilBERT model, we offer a complete framework to assess the overall credibility of campaigns.

The primary indicators of fraudulent campaigns – sentiment of the campaign descriptions, frequency of the category-based keywords, update count, and presence of a campaign beneficiary – were evaluated individually to assess the likelihood of a campaign being fraudulent. The trained DistilBERT model was utilized to assess the description of a campaign and return a sentiment score that corresponded to the fraud likelihood.

As stated in the results section, these four factors were then combined with varying weight values, to obtain a final total score that reflects the probability of the campaign under consideration being fraudulent.

These factors were weighted according to their determined importance. This offers a customizable approach that can be adapted according to the specific priorities of future researchers.

As the field evolves, future work could involve refining the considered indicators and including more attributes of these campaigns, expanding the geographical scope of the study, and exploring multiple models and their combinations. This study lays the groundwork for more secure digital fundraising environments, ultimately fostering a safer space for online philanthropy.

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VII.References

[1] Statista, "Worldwide reward-based crowdfunding market size," *Digital Capital Raising: Reward-based Crowdfunding – Worldwide*. [Online]. Available:
[2] https://www.statista.com/outlook/fmo/capital-raising/digital-capital-raising/reward-based-crowdfunding/worldwide?currency=usd.
[3] *Peer-reviewed article that supports GoFundMe's claims of being the largest crowdfunding platform*, JAMA Network Open. [Online]. Available: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/277216 0.
[4] A. Harris, "GoFundMe keeps gobbling up competitors, says it's 'very good for the market'," *Fast Company*, Apr. 4, 2018. Accessed Nov. 23, 2019. [Online]. Available: https://www.fastcompany.com/40554199/gofundme-keeps-gobbling-up-competitors-says-its-very-good-for-the-market.
[5] GoFraudMe. [Online]. Available: https://gofraudme.com/
[6] Reddit website. [Online]. Available: https://www.reddit.com.
[7] E. Mollick, "The dynamics of crowdfunding: An exploratory study," *Journal of Business Venturing*, vol. 29, no. 1, pp. 1–16, 2014.
[8] I. H. Kenang and G. Gosal, "Factors affecting online donation intention in donation-based crowdfunding," *The Winners*, vol. 22, no. 2, pp.97–104, 2021. doi: 10.21512/tw. v22i2.7101.
[9] Suresh, G. V., & Sudhakar, K. (2024). Different Machine Learning Approaches for Fake News Detection. *International Journal of Computer Science and Mechatronics*, 10(2).
[10] Satish, G. Y., Kumar, M. A., & Sudhakar, K. (2021). Emotion Recognition on Twitter: Comparative Study and Training a Unison Model. *International Journal of Computer Science & Mechatronics-IJCSM*, 7(6), 1–5.
[11] Sudhakar, K., Meghana, A. M. M., Santoshi, T. G., Balaji, M. P., & Rajarajeswari, A. J. (2022). Articles Recommendation System Using NLP Techniques. *Parishodh Journal*, 11(6), 51–58.

[12] Khullar, S., Kumar, B. A., Karumanchi, D. R., Venugopalarao, G., Sudhakar, K., & Raju, M. V. (2026). Hybrid Embedding and Transformer-based Text and Vision Architectures for Deep Learning Artificial Intelligence. *2026 6th International Conference on Expert Clouds and Applications (ICOECA)*, 1412–1417. IEEE.

[13] Sudhakar, K., & Gupta, J. N. (2019). Data Analytics on Consumer Behavior in Credit Card Industry. *Journal of Emerging Technologies and Innovative Research*, 6(3), 334–338.

[14] Balamurugan, A., GIriranjan, B., Sudhakar, K., Potluri, P., Kumar, K. R., & Sane, A. R. (2022). Data Management and Visual Information Processing in Financial Organisation using Machine Learning. *2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*.

[15] Sudhakar, K., N, A., Biradar, S., Indira, B., Basha, S. S., & T, K. (2021). Empirical View Of Financial Management Survey In Block Chain Technology Issues, Risk And Mitigation. *International Journal of Aquatic Science-IJAS*, 12(1), 259–267.

[16] Mahalakshmi, N. V., Tejaswini, G., & Sudhakar, K. (2020). Feature Selection, based on teaching and learning based Optimization Algorithm. *International Journal of Computer Science & Mechatronics-IJCSM*, 1(1), 1–8.

[17] Sudhakar, K., Lavanya Valli, P., Charitha, V., Sasi Durga, G., & Sri Sai Leela, P. (2021). Data Poison detection schemes for Distributed Machine Learning. *Mukt Shabd Journal*, 10(7), 572–577.

[18] Sudhakar, K., Sree, S. C., Meghana, L., Bhavana, S., & Durga, B. N. (2022). Identification of types of intrusion attacks using spark and gradient boosted tree classifier. *International Journal For Innovative Engineering and Management Research*, 11(4), 49–55.

[19] B. Perez *et al.*, "I Call BS: Fraud detection in crowdfunding campaigns," in *Proc. 14th ACM Web Sci. Conf.*, 2022.

[20] The Stanford Natural Language Processing Group. [Online]. Available: https://nlp.stanford.edu/

[21] J. O. Awoyemi, A. O. Adetunmbi, and S. A. Oluwadare, "Credit card fraud detection using machine learning techniques: A comparative analysis," in *Proc. 2017 Int. Conf. Comput. Netw. Informatics (ICCNI)*, Oct. 2017, pp. 1–9.

[22] J. Duarte, S. Siegel, and L. Young, "Trust and credit: The role of appearance in peer-to-peer lending," *The Review of Financial Studies*, vol. 25, no. 8, pp. 2455-2484, 2012.

[23] A. Agrawal, C. Catalini, and A. Goldfarb, "Some simple economics of crowdfunding," *Innovation Policy and the Economy*, vol. 14, no. 1, pp. 63–97, 2014. [Online]. Available: https://sci-hub.se/https://www.sciencedirect.com/science/article/abs/pii/ S0167624515000463? via%3Dihub.

[24] Indian School of Business, "Donation-based digital crowdfunding: The changing face of giving in India." [Online].Available:https://www.isb.edu/content/dam/sites/managementrethink/Donation%20based%20Digital%20CrowdfundingThe%20Changing%20Face%20of%20Giving%20in%20India.pdf.coredownload.pdf.

[25] "Fraud," *Legal Information Institute*, Cornell Law School. [Online]Available:https://www.law.cornell.edu/wex/fraud.

[26] Q. Gao and M. Lin, "Economic value of texts: Evidence from online debt crowdfunding," in *Proc. Conf. Financial Innovation: Online Lending to Households and Small Businesses*, Washington, DC, USA, 3 Dec. 2016.

[27] D. Cumming, L. Hornuf, M. Karami, and D. Schweizer, "Disentangling crowdfunding from fraudfunding," *J. Bus. Ethics*, pp. 1–26, 2021.

[28] GoFundMe, "About us," *GoFundMe*. [Online]. Available:https://www.gofundme.com/c/about-us

[29] M. Wade, "The giving layer of the internet: A critical history of GoFundMe's reputation management, platform governance, and communication strategies in capturing peer-to-peer and charitable giving markets," *Journal of Philanthropy and Marketing*, vol. 28, Oct. 2022, doi: 10.1002/nvsm.1777.