*A Comprehensive Survey On SASM Using NLP & Machine Learning*

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*Abstract*—*Social Media platforms are a rich source of unstructured textual data that can provide valuable insights into public sentiment. In this project, we propose a comprehensive approach to sentiment analysis on social media data. We utilize APIs to collect data, employ JDBC (Java Data Base Connectivity) for efficient data storage, leverage Natural Language Processing (NLP) techniques to preprocess and extract features from text, and apply Machine Learning (ML) algorithms to classify sentiment. In essence, our sentiment analysis project was born out of a recognition of the potential of social media data and the need to harness advanced technologies to make sense of this vast and unstructured information while upholding ethical principles in data handling. The final output is presented through interactive visualizations using JavaScript libraries like chart.js. This project aims to offer a holistic solution for sentiment analysis, enabling users to gain insights into public opinion and sentiment trends on various social media platforms*

Keywords—

# Introduction

In today’s digital age, social media platforms have emerged as a goldmine of unstructured text data, reflecting the collective sentiments, o­­pinions, and emotions of millions of users worldwide. This project embarks on the fascinating journey of sentiment analysis, a crucial aspect of Natural Language Processing (NLP) and Machine Learning (ML).

By integrating APIs for data collection and JDBC for efficient data storage, this project harnesses modern technology to analyze and categorize the emotional tones present in social media conversations. The heart of the project lies in NLP, where textual data undergoes thorough processing, cleansing, and transformation into features that can be fed into ML algorithms. These algorithms, trained to understand and classify sentiment, enable the project to categorize text as positive, negative, or neutral, offering a nuanced understanding of the emotional context within the data.Moreover, the project extends its scope to data visualization, utilizing JavaScript libraries like chart.js. Through interactive charts and graphs, it aims to present sentiment analysis results in visually compelling and comprehensible manner. These visualizations not only serve as presentation tools but also empower users to explore and interpret sentiment trends over time, across various sources, or within specific contexts.In summary, this project serves as a bridge between the wealth of unstructured social media data and actionable insights. By offering a comprehensive solution encompassing data collection, storage, preprocessing, sentiment analysis, and visualization, it empowers users to unlock the latent value within digital conversations. As we delve deeper into the project’s components, we will uncover the intricate processes that make it a robust and valuable tool for understanding public sentiment in the digital-era.

Its primary aim is to decipher the sentiments expressed within social media data, providing valuable insights for businesses, organizations, and data analysts.

# Backgroung Study

Our sentiment analysis project has its roots in recognizing the growing importance of social media data in today's digital landscape. The exponential increase in user-generated content on platforms like Twitter, Facebook, and Instagram has made it a treasure trove of information. However, this data comes in the form of unstructured text, making it challenging to extract meaningful insights. Recognizing this challenge, our project was conceived to address these issues and provide actionable sentiment insights.

To lay the foundation for our project, extensive research was conducted in the field of Natural Language Processing (NLP), Machine Learning (ML), and data visualization. We reviewed existing sentiment analysis methodologies and techniques, studying the works of both academia and industry leaders in the domain. This research phase was crucial in identifying the best practices and methodologies that could be integrated into our project. Moreover, ethical considerations were a significant focus during the project's planning phase. We examined guidelines and ethical standards for handling user-generated content and personal data, ensuring that our project adhered to responsible data collection and usage practices. In our pursuit of developing an effective sentiment analysis solution, we delved deeper into the challenges posed by unstructured textual data. It became evident that the sheer volume of social media content, coupled with the nuances of language, required advanced NLP techniques to accurately gauge sentiment. We explored various sentiment lexicons, machine learning algorithms, and deep learning models to understand their strengths and limitations in this context. This exploration was pivotal in selecting the most suitable tools and approaches for our project. Furthermore, as the digital landscape evolves rapidly, the need for real-time insights became increasingly apparent. The project's background study included an examination of emerging trends in social media analytics and real-time data processing. We studied the integration of streaming data platforms, such as Apache Kafka and Apache Flink, to ensure that our system could provide up-to-the-minute sentiment analysis, a crucial requirement for businesses and organizations seeking to stay ahead in the fast-paced digital world. Additionally, our ethical considerations extended to examining global data protection regulations, privacy policies, and industry standards governing social media data usage. This comprehensive understanding of the legal and ethical landscape helped shape our project's data handling and user privacy protection strategies. In conclusion, our sentiment analysis project has its origins in a deep-seated recognition of the transformative potential of social media data, coupled with the challenges it presents in its unstructured form. Through extensive research and analysis, we have identified the pivotal role of advanced technologies in addressing these challenges, including Natural Language Processing (NLP), Machine Learning (ML), and real-time data processing. Additionally, our commitment to ethical data handling practices ensures that our project aligns with global regulations and standards, safeguarding user privacy and promoting responsible data usage.

RELATED WORK

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# Related Work

[1] Mameli M, Paolanti M, Morbidoni C, Frontoni E & Teti A (2022) discusses the design and implementation of a social media analytics system called SocMINT, which provides a visual dashboard to monitor and analyze social media conversations on specific topics. The system aggregates data from multiple social sources and performs sentiment analysis on textual, visual, and mixed content using a neural network architecture. The paper includes a real-world case study where the system was used to analyze candidates political communication on Facebook, Instagram, and Twitter. The authors also discuss the benefits of real-time analysis of social media for politicians and news agencies, as well as the challenges in analyzing online conversations.

[2]S.A.Alshehri,A.A.Almohammadi,M.A.Alghamdi, presents a sentiment analysis system for social media that considers the impact of lengthened words. The authors highlight the importance of accurate interpretation of social media communication and how it can impact decision-making. They propose a new sentiment analysis system based on lexicon that considers the lengthened words and evaluate its performance on precision, recall, and F-measures. The proposed system is compared with traditional systems that ignore the lengthened words to validate its performance and accuracy. The study confirms the strong impact of lengthened words in sentiment analysis and the critical need to correctly detect these words to provide complete coverage.

[3] Christofer Laurell and Christian Sandstrom. explores the potential of Social Media Analytics (SMA) as a tool for external search and open foresight. The authors present a case study Tesla’s autopilot and regulatory scrutiny of autonomous driving to demonstrate the effectiveness of SMA in monitoring development and gaining knowledge without being overwhelmed by information overload. The study is limited by the choice of platforms, language, and time frame, but the authors encourage further research into the topic and modifications to the approach. Overall, the paper suggests that SMA can be valuable for firms in an uncertain and complex business environment.

[4] Jie Tong, Leilei Shi, Lu Liu,John Pannerselvam, and Zixuan Han, proposed a novel influence maximization algorithm for a competitive environment based on social media data analytics. The authors explore the problem of influence maximization in a multichannel information transmission network with competitive relationships. They propose a solution that considers the local community discovery algorithm is evaluated using a Twitter dataset and is found to be efficient and accurate in influence discovery and maximization.

[5] Md. Saifur Rahman and Hassan Reza, is a systematic review of big data analytics in social media by Md.Saifur Rahman and Hassan Reza. The authors propose the “Sunflower Model of Big Data” and identify the top ten social data analytics for social media platforms. The study highlights the significance of social media data in decision making process and provides a taxonomy of big data analytics in social media. The paper also evaluates the work by addressing the research questions and discusses potential challenges and limitation.

[6] Minzheng Xuanyuan, Le Xiao, and Mengshi Duan, proposes a sentiment classification for short-term and small-scale data scenarios in public opinion analysis. The algorithm uses multi-modal social media text information and user attributes to improve accuracy without sacrificing data and training time. The proposed method , called User attributes Convolution and Recurrent Neural Network (UCRNN), combines parallel convolutional neural networks (CNN) and Recurrent Neural Network (RNN) to process text information and uses user attributes respectively. The experiments verify that the training time of this model is slightly less than TextRNN, and the classification accuracy can reach 90.2%, which is the state-of-the-art in the field of short-term and small scale data sentiment classification.

[7] Achraf Boumhidi, Abdessamad Benlahbib, and El Habib Nfaoui, proposed a cross-platform reputation generation system based on aspect-based sentiment analysis (ABSA) to process online opinions and reviews. The system includes components for collecting and standardizing opinions from different platforms, filtering out spam, extracting and analyzing aspects within textual opinions, and calculating reputation values for the targeted entity and its aspects based on review time and popularity. The proposed system is designed to generate numerical reputation values for a specific item (product, movie, service, hotel, etc.) and its aspects based on opinions and reviews expressed online.

[8] Fernando Arias, Maytee Zambrano Nunez, Ariel Guerra-Adames focuses on sentiment analysis (SA) techniques and their applications to human health. It provides a wide contextualization, classification, and categorization of scientific production in knowledge of AI theories, models, and algorithmic techniques focused on the pandemic study of various viruses. The paper offers different possibilities of understanding the problem treated and more than one study alternative. The authors have deliberately chosen to focus on techniques related to the extraction and classification of linguistic information. The study concludes that interdisciplinary groups of medical specialists and technologists need to integrate their specialities to analyze and contribute ideas that clarify linesof action in the face of the COVID-19 pandemic and other pandemic that have affected the world’s population.

[9] Yao Houkpati, Staphord Bengesi, Timothy Oladunni, Halima Audu, Ruth Olusegun This paper focuses on the analysis of emotions expressed on social media during the monkeypox outbreak. The authors extract and preprocess a dataset of 800,000 tweets related to monkeypox and use the NRCLexicon library to measure the emotional significance of each text. They develop deep learning models, including CNN, LSTM, BiLSTM, and CLSTM, for emotion classification. The models are trained using oversampling and undersampling techniques to address class imbalance. The results show that the CNN model achieves the highest accuracy of 96% in emotion classification. The study highlights the importance of understanding public emotions during disease outbreaks and suggests that emotion classification can contribute to effective interventions and public health improvement. The paper also discusses future directions, such as analyzi ng temporal trends of emotions and exploring the relationship between languages and emotions in tweets.

[10] Z . Stapić, E. G. López, A. G. Cabot, L. de Marcos Ortega,and V. Strahonja,, is a systematic review on implicit and explicit aspect extraction in sentiment analysis. It consists of three major phases: planning review, conducting the systematic review, and mapping the challenges associated with aspect extraction techniques. The review aims to identify the techniques used for aspect extraction, analyze evaluation metrics and data domains, highlight the challenges, and suggest future research directions. The review selected online databases such as ACM, DBLP, IEEE Xplore, Science-Direct, Springer-Link, Scopus, and Web of Science to discover relevant studies. A total of 94 articles were chosen for the review. The paper also mentions different aspect extraction techniques and their limitations.

[11] Anna Nguyen, Antonio Longa, Massimiliano Luca, Joe Kaul, Gabriel Lopez,proposes a novel algorithm called the Multi-Lyered Tweet Analyzer (MLTA) for group-level emotion analysis of Twitter data. The MLTAutilizes multi-layered networks (MLNs) to social media text and extract information from the Tweet-MLN and make predictions based on the extracted graph features.The results show that

the MLTA can predict a wider range of emotions and achieve accurate group level predictions. The paper also conducts an ablation study to compare different graph convolution layers and establishes a baseline for graph-level classification on MLNs

[12] Loris Belcastro, Riccardo Cantini, Fabrizio Marozzo, Domenico Talia, and Paolo Trunfio , presents a methodology called IOM-NN (Iterative Opinion Mining using Neural Networks) for analyzing the polarization of social media users during election campaigns. The methodology uses an automatic incremental procedure based on neural networks to classify posts and determine the polarization of users towards a specific faction. The proposed approach has been tested on two case studies, the 2018 Italian general election and the 2016 US presidential election, and has shown high accuracy compared to opinion polls and other existing techniques.

[13] Lin Yue, Weitong Chen, Xue Li, Wanli Zuo, Minghao Yin, provides an overview of the progress, advances, and limitations in this area, with a focus on presenting typical methods from three different perspectives (task-oriented, granularity-oriented, methodology-oriented). The paper categorizes and compares a large quantity of techniques and methods, and introduces different types of data and advanced tools for research, as well as their limitations. The available benchmark datasets are discussed and then

categorized according to their usage in certain applications. The paper proposes novel multiple perspectives, teases out series of works, organizes tools, and benchmarks datasets used in various works, making it a valuable resource for beginners and researchers in the field

[14] Dharmendra Dangi,Dheeraj K. Dixit,Amit Bhagat review the relevant works in the area of COVID-19 analysis and highlight the limitations of current research in this area. They propose a novel approach called Sentimental Analysis of Twitter social media Data (SATD) that uses five different machine learning models to enhance the accuracy of sentimental analysis. The paper also describes the data collection and labeling process, as well as the experimental analysis and results. Overall, the paper provides a comprehensive overview of the current state of research in this area and presents a promising approach for sentiment analysis of COVID-19 social media data.

[15] Ferdaous Benrouba, Rachid Boudour, proposes an approach to filter social media content that could be emotionally harmful to the user by using sentiment analysis. The literature survey in the paper explores original research on the topic of emotion detection using artificial intelligence filters. The survey highlights the importance of emotion models in text-based emotion detection on social media platforms. The paper also discusses previous research on sentiment analysis techniques used to analyze tweets collected from Twitter users in the United Arab Emirates (UAE) to measure happiness, and to classify user-generated content on Twitter (tweets) as a binary classification (extremist tweets or non-extremist tweets). Additionally, the paper mentions a deep learning-based domestic violence identification system and sentiment analysis techniques used to predict the result of the Indonesian presidential election.

[16]Rachna Jain, Ashish Kumar,Anand Nayyar,Kritika Dewan,Rishika Garg,Shatakshi Raman,Sahil Ganguly, provides a literature survey on the subject of explainability and interpretability in artificial intelligence models, specifically in the context of sentiment analysis. The authors discuss recent research on the subject, including benchmarking various machine learning algorithms, analyzing global feature importance, and identifying reasons behind prediction bias. They also highlight the shortcomings of previous research, such as small dataset sizes, exclusion of deep learning methods, and limited evaluation metrics. Overall, the paper aims to contribute to the growing body of work on explainable AI and provide a unique approach to visualizing sentiment analysis results.

[17] Ahmed Alsayat,, proposes a novel approach to sentence-level classification using parallel fuzzy deep learning classifiers. The approach involves data preprocessing techniques to enhance the quality of the given dataset, word embeddings methods to transform texts into numerical data, and deep learning methods to compute the NSS and PSS. The fuzzy logic theory is then applied as the fuzzy classifier to classify the sentences into three labels: negative, neutral, and positive. The Hadoop framework is used to parallelize the introduced FDLC to avoid long execution time issues. Multiple experiments are carried out to prove the effectiveness of the suggested model, and it is compared with several selected classifiers from the literature. The experimental results indicate that the suggested model achieves a better classification rate than the other classifiers on the given dataset. The contribution of this work is fundamentally incarnated into six aspects, including data preprocessing techniques, word embeddings methods, and deep learning methods. The proposed approach has potential applications in the field of natural language processing, particularly in sentiment analysis.

[18] Fatima Es Sabery, Abdellatif Hair, Junaid Qadir, Beatriz Sainz De Abajo, proposes a novel approach to multimodal sentiment analysis using a deep multi-view attentive network of image and text data. The proposed approach incorporates two distinct visual attention branches to investigate visual characteristics at the region and scene levels, enabling textual information to guide the learning process for visual features and vice versa. Cross-modal fusion learning is designed to integrate the various features within a comprehensive framework to identify the complementary aspects across multiple modalities. Multi-head attention facilitates the extraction and fusion of adequate information in the intermediate features. Finally, an MLP with stacking-fully connected layers is used to classify sentiment by deeply fusing the modal features. An interpretable multimodal sentiment classification model based on LIME is developed to expose the internal model dynamics and visualize the association between the instance’s characteristics and the model’s prediction. Extensive experiments on real-world sentiment and emotion datasets are carried out to demonstrate the proposed model’s effectiveness through comparisons with previous models. The proposed approach outperforms existing methods in terms of accuracy and interpretability.

[19] Israa Khalaf Salman Al Tameemi, Mohammad Reza, Saeid Pashazadeh, proposes a Multi-Attention Fusion (Multi-AFM) model for sentiment analysis of educational big data. The model integrates global and local attention to improve classification results in teaching evaluation. The local attention calculation method uses a dependency tree to extract the attention score of a sentence in a specific aspect. A gating unit is proposed for controlling the weights in the fusion of global and local attention. Experimental results show that the Multi-AFM model performs better than existing attention models in education and other fields. The paper discusses previous research about attention-based methods for sentiment analysis. The proposed model uses a bidirectional LSTM to generate the sentence representation of the embedded aspect. The global and local attention corresponding to the embedded sentences are generated respectively, and the gating mechanism is used to control the fusion of global and local attention. Finally, the result is fed to the Softmax classifier for final classification. The paper concludes by summarizing the main contributions of the work and discussing future research directions.

[20] Guanlin Zhai, Yan Yang, Heng Wang, and Shengdong Du, proposes an ensemble deep learning model for sentiment analysis in social media applications, with a focus on the COVID-19 pandemic. The model combines a customized deep learning model with advanced word embedding techniques and a long short-term memory network. The proposed model is evaluated on various social media datasets and compared with other state-of-the-art classifiers. The results show that the ensemble model outperforms the baseline classifier and other state-of-the-art classifiers. The paper also provides an extensive review of related works on sentiment analysis and its applications. The study highlights the importance of sentiment analysis in social media applications and its potential impact on public health during the pandemic. The proposed model can be used to monitor public sentiment towards COVID-19

and other topics of interest. The paper concludes that the proposed ensemble model can improve the accuracy and efficiency of sentiment analysis in social media application.

## Abbreviations and Acronyms

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

## Units

* Use either SI (MKS) or CGS as primary units. (SI units are encouraged.) English units may be used as secondary units (in parentheses). An exception would be the use of English units as identifiers in trade, such as “3.5-inch disk drive”.
* Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.
* Do not mix complete spellings and abbreviations of units: “Wb/m2” or “webers per square meter”, not “webers/m2”. Spell out units when they appear in text: “. . . a few henries”, not “. . . a few H”.
* Use a zero before decimal points: “0.25”, not “.25”. Use “cm3”, not “cc”. (*bullet list*)

## Equations

The equations are an exception to the prescribed specifications of this template. You will need to determine whether or not your equation should be typed using either the Times New Roman or the Symbol font (please no other font). To create multileveled equations, it may be necessary to treat the equation as a graphic and insert it into the text after your paper is styled.

Number equations consecutively. Equation numbers, within parentheses, are to position flush right, as in (1), using a right tab stop. To make your equations more compact, you may use the solidus ( / ), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

*a**b* 

Note that the equation is centered using a center tab stop. Be sure that the symbols in your equation have been defined before or immediately following the equation. Use “(1)”, not “Eq. (1)” or “equation (1)”, except at the beginning of a sentence: “Equation (1) is . . .”

## Some Common Mistakes

* The word “data” is plural, not singular.
* The subscript for the permeability of vacuum **0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter “o”.
* In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
* A graph within a graph is an “inset”, not an “insert”. The word alternatively is preferred to the word “alternately” (unless you really mean something that alternates).
* Do not use the word “essentially” to mean “approximately” or “effectively”.
* In your paper title, if the words “that uses” can accurately replace the word “using”, capitalize the “u”; if not, keep using lower-cased.
* Be aware of the different meanings of the homophones “affect” and “effect”, “complement” and “compliment”, “discreet” and “discrete”, “principal” and “principle”.
* Do not confuse “imply” and “infer”.
* The prefix “non” is not a word; it should be joined to the word it modifies, usually without a hyphen.
* There is no period after the “et” in the Latin abbreviation “et al.”.
* The abbreviation “i.e.” means “that is”, and the abbreviation “e.g.” means “for example”.

An excellent style manual for science writers is [7].

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## Authors and Affiliations

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#### Selection: Highlight all author and affiliation lines.

#### Change number of columns: Select the Columns icon from the MS Word Standard toolbar and then select the correct number of columns from the selection palette.

#### Deletion: Delete the author and affiliation lines for the extra authors.

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Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is “Heading 5”. Use “figure caption” for your Figure captions, and “table head” for your table title. Run-in heads, such as “Abstract”, will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced. Styles named “Heading 1”, “Heading 2”, “Heading 3”, and “Heading 4” are prescribed.

## Figures and Tables

#### Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation “Fig. 1”, even at the beginning of a sentence.

1. Table Type Styles

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| Table column subhead | Subhead | Subhead |
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1. Sample of a Table footnote. (*Table footnote*)

We suggest that you use a text box to insert a graphic (which is ideally a 300 dpi TIFF or EPS file, with all fonts embedded) because, in an MSW document, this method is somewhat more stable than directly inserting a picture.

To have non-visible rules on your frame, use the MSWord “Format” pull-down menu, select Text Box > Colors and Lines to choose No Fill and No Line.

1. Example of a figure caption. (*figure caption*)

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity “Magnetization”, or “Magnetization, M”, not just “M”. If including units in the label, present them within parentheses. Do not label axes only with units. In the example, write “Magnetization (A/m)” or “Magnetization {A[m(1)]}”, not just “A/m”. Do not label axes with a ratio of quantities and units. For example, write “Temperature (K)”, not “Temperature/K”.

##### Acknowledgment *(Heading 5)*

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

##### References

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Number footnotes separately in superscripts. Place the actual footnote at the bottom of the column in which it was cited. Do not put footnotes in the abstract or reference list. Use letters for table footnotes.

Unless there are six authors or more give all authors’ names; do not use “et al.”. Papers that have not been published, even if they have been submitted for publication, should be cited as “unpublished” [4]. Papers that have been accepted for publication should be cited as “in press” [5]. Capitalize only the first word in a paper title, except for proper nouns and element symbols.

For papers published in translation journals, please give the English citation first, followed by the original foreign-language citation [6].

1. G. Eason, B. Noble, and I. N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955. *(references)*
2. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.
3. I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.
4. K. Elissa, “Title of paper if known,” unpublished.
5. R. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.
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7. M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

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