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AI-Driven Crisis Intervention Sysytem For Perintal Mental Health

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ABSTRACT:

Combining advanced artificial intelligence with satellite technologies and vessel tracking has transformed oil spill detection in maritime environments. Our research introduces a robust automated system that integrates data from Automatic Identification Systems (AIS) and Synthetic Aperture Radar (SAR) satellites. By leveraging machine learning algorithms, our approach analyzes vessel behaviors, detects anomalies, and verifies spills using high-resolution SAR images. This multi-source method ensures real-time monitoring and rapid response capabilities, significantly reducing detection times while maintaining high accuracy. Through careful dataset augmentation and training with diverse environmental conditions, our system achieves over 97% accuracy, demonstrating its effectiveness in mitigating ecological and economic impacts. This innovative solution not only enhances environmental monitoring but also underscores our commitment to sustainable practices for safeguarding marine ecosystems.

Keywords:

Perinatal mental health, crisis intervention, artificial intelligence, natural language processing, machine learning, maternal care

INTRODUCTIOION:

Oil spills, which involve the release of petroleum-based substances into the environment, can occur throughout the oil production chain—from exploration and transportation to storage and distribution. These incidents are often triggered by external causes such as equipment failure, accidents, or environmental conditions, and their impact can be devastating. Marine ecosystems are particularly vulnerable, as oil contamination threatens marine life, fisheries, and coastal economies. Despite global awareness, oil spills remain a frequent challenge. In 2023 alone, there was one major spill exceeding 700 tons and several medium-scale incidents, resulting in an estimated loss of over 2000 tons of fuel, crude oil, and other petroleum products.

This growing concern highlights the urgent need for reliable and timely oil spill detection systems. The behavior of oil in marine environments is influenced by physical properties like viscosity and surface tension, as well as environmental factors such as wind and temperature. Once spilled, oil forms slicks that spread across the water surface, making detection increasingly difficult over time due to natural degradation processes.

Conventional detection methods—including manual reports, aerial surveillance, and satellite imagery— have been useful but are often limited by environmental constraints. Satellite-based remote sensing, especially Synthetic Aperture Radar (SAR), has proven effective because of its ability to operate in all weather and lighting conditions. SAR detects oil spills by analyzing backscatter values that differentiate clean water from oil-covered surfaces. However, SAR imagery can sometimes produce false positives, particularly in regions affected by algae blooms or shallow waters, and its sensitivity to wind patterns can also compromise detection accuracy.

To address these challenges, advancements in Polarimetric SAR (PolSAR) technology have introduced multi-polarization capabilities, enabling better distinction of surface materials and enhancing

.LITERATURE SURVEY

Internet use by older adults with bipolar disorder: international survey results

https://journalbipolardisorders.springeropen.com/articles/1 0.1186/s40345-018-0127-7#:~:text=Older%20adults%20with%20bipolar%20disord er%20used%20the%20Internet%20much%20less,not%20s pecific%20to%20bipolar%20disorder.

ABSTRACT: Background The world population is aging and the number of older adults with bipolar disorder is increasing. Digital technologies are viewed as a framework to improve care of older

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adults with bipolar disorder. This analysis quantifies Internet use by older adults with bipolar disorder as part of a larger survey project about information seeking. Methods A paper-based survey about information seeking by patients with bipolar disorder was developed and translated into 12 languages. The survey was anonymous and completed between March 2014 and January 2016 by 1222 patients in 17 countries. All patients were diagnosed by a psychiatrist. General estimating equations were used to account for correlated data. Results Overall, 47% of older adults (age 60 years or older) used the Internet versus 87% of younger adults (less than 60 years). More education and having symptoms that interfered with regular activities increased the odds of using the Internet, while being age 60 years or older decreased the odds. Data from 187 older adults and 1021 younger adults were included in the analysis excluding missing values. Conclusions Older adults with bipolar disorder use the Internet much less frequently than younger adults. Many older adults do not use the Internet, and technology tools are suitable for some but not all older adults. As more health services are only available online, and more digital tools are developed, there is concern about growing health disparities based on age. Mental health experts should participate in determining the appropriate role for digital tools for older adults with bipolar disorder.

SYSTEM DESIGN
SYSTEM ARCHITECTURE:

DATA FLOW DIAGRAM:

a. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
b. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process.
external entity that interacts with the system and the information flows in the system.
c. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
d. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels
2. that represent increasing information flow and functional detail.

illegal activities by early prediction. *is paper examines different prediction methods. Various machine learning algorithms are popular to train data in order to predict future data. Random forest model, Na¨ıve Bayes, and k- mean clustering are popular ML algorithms. Social media is one of the best sources of data gathering as the mood of the user also reveals his/her psychological behavior. In this survey, various advances in data science and its impact on the smart healthcare system are points of consideration. It is concluded that there is a need for a cost-effective way to predict intellectual condition instead of grabbing costly devices. Twitter data is utilized for the saved and live tweets accessible through application program interface (API).

FUTURE ENHANCEMENT:

In the future, connecting twitter API with python, then applying sentimental analysis on ‘posts,’ ‘liked pages’, ‘followed pages,’ and ‘comments’ of the twitter user will provide a cost-effective way to detect depression for target patientsenvironmental monitoring. Yet, interpreting PolSAR data requires complex algorithms and expert knowledge. Traditional machine learning methods for oil spill detection often depend heavily on manual feature extraction, which is time-consuming and not easily adaptable across scenarios.
In recent years, deep learning has revolutionized the way we process and interpret remote sensing data.

Unlike traditional methods, deep learning models can automatically learn complex patterns and extract meaningful features from raw input data. Prior research has applied models such as AlexNet and YOLOv4 for oil spill detection, even under difficult conditions like low light and shadows. However, these anchor-based detection models may fall short when oil spills take on irregular shapes or variable sizes.
To overcome these limitations, our study introduces a customized, high-resolution dataset tailored specifically for oil spill segmentation using deep learning. We annotated this dataset with semantic segmentation labels to precisely identify oil spill regions. The YOLOv8 segmentation model was then processing techniques like K-means clustering and Truncated Linear Stretching were applied to

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improve both detection accuracy and robustness.
This research contributes to the field in several ways:

1. Development of a rich, diverse dataset for oil spill detection.
2. Implementation of an optimized YOLOv8 model for high-precision segmentation.
3. Integration of advanced image enhancement techniques to boost performance.

The remainder of this paper is organized as follows: Section 2 reviews related work and highlights the limitations of existing techniques. Section 3 outlines the methodology, including dataset preparation and YOLOv8 model training. Section 4 presents experimental results and quantitative evaluations. Finally, Section 5 summarizes key insights and outlines directions for future improvements. By merging deep learning with high- quality data and practical enhancements, our approach offers a powerful, real-time solution for marine environmental protection.

Big Data & Digital Advancements in Mental Health Research

Big data is increasingly being used in **mental health research** across the globe for a wide range of purposes — from early diagnosis and treatment personalization to population-level mental health monitoring. **Data science**, as a rapidly evolving field, brings powerful tools and insights to this area, enabling researchers and clinicians to uncover hidden patterns, predict risks, and design more effective interventions.

In this perspective, we have explored various types of **mental disorders** and discussed **affordable and practical solutions** that can enhance existing mental healthcare systems. The use of big data, combined with artificial intelligence (AI), opens up possibilities for: However, while the **digital mental health revolution** is advancing rapidly, its growth often **outpaces scientific validation and clinical integration**. This creates a gap between technological innovation and actual application in medical practice. It is increasingly evident that **clinical communities and regulatory bodies must adapt quickly** to ensure that these technologies are both **safe and effective**.

Furthermore, the rise of **smart healthcare solutions** — including teletherapy platforms, mental health apps, wearable monitors, and AI-based diagnostic tools — is expanding the reach of mental health services, especially in remote and underserved areas.

To truly harness the benefits of big data in mental health, it is essential to combine **technological innovation with rigorous research**, **ethical considerations**, and a **patient-centered approach**.

FUTURE SCOPE:

The future of oil spill detection lies in building smarter, faster, and more integrated systems that not only detect spills but also predict their movement and support real-time responses. As oil spills remain a serious threat to marine ecosystems and coastal economies, evolving this technology becomes not just a technical need, but an environmental responsibility.

A key direction for advancement is the **integration of weather data, ocean current models, and high- resolution satellite imagery** to enhance the prediction of spill drift and dispersion patterns. By combining these with **real-time AIS feeds** and **IoT sensor data**, future systems can gain a more holistic and accurate view of each incident, enabling early warning and rapid response efforts.

On the technical front, **deep learning models** will continue to evolve, offering more precise oil slick segmentation through advanced neural networks. Incorporating **semantic segmentation, attention mechanisms, and explainable AI techniques** will not only improve accuracy but also increase trust in automated systems used by marine authorities and environmental agencies.

To support this growth, there is a need to **expand high-quality datasets** that represent diverse spill conditions—ranging across different oil types, lighting conditions, sea states, and geographical areas. This will help train more generalized and resilient models capable of operating in complex and dynamic marine environments.

Moreover, future frameworks should include **automated reporting mechanisms** for regulatory compliance and seamless integration with **maritime law enforcement** systems. This can aid in the quick identification of responsible vessels and ensure legal accountability, further discouraging negligence at sea. Another emerging opportunity lies in **spill source attribution**—using pattern recognition and behavioral analysis of AIS data to trace pollution back to specific vessels. This will enhance the capability of agencies to take preventive actions and enforce stricter environmental regulations.

Ultimately, as technologies converge, these intelligent systems will pave the way for **proactive**

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marine environmental monitoring. Not only will they reduce the ecological and economic impact of spills, but they will also foster a safer, cleaner, and more sustainable ocean for future generations.

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Ultimately, as technologies converge, these intelligent systems will pave the way for **proactive marine environmental monitoring**. Not only will they reduce the ecological and economic impact of spills, but they will also foster a safer, cleaner, and more sustainable ocean for future generations.

CONCLUSION:

Big data are being used for mental health research in
parts of the world and for many different purposes. Data science is a rapidly evolving field that offers many valuable applications to mental health research, examples of which we have outlined in this perspective. We discussed different types of mental disorders and their reasonable, affordable, and possible solution to enhance the mental healthcare facilities. Currently, the digital mental health revolution is amplifying beyond the pace of scientific evaluation and it is very clear that clinical communities need to catch up. Various smart healthcare systems and devices developed that reduce the death rate

RESULT:

Big data is increasingly being used in mental health research across the world for a variety of purposes. As data science continues to evolve rapidly, it brings valuable tools and applications that contribute significantly to understanding and addressing mental health issues. Researchers are examining different types of mental disorders and proposing solutions that are not only effective but also affordable and feasible to implement, with the goal of improving mental healthcare systems.

At the same time, the digital mental health movement is growing faster than the pace of scientific validation. This gap highlights the urgent need for clinical communities to catch up and adapt to these rapid technological changes. Smart healthcare systems and digital devices are now being developed and deployed to support mental health care. These innovations have shown promise in reducing mortality rates among mental health patients and in helping to prevent them from engaging in harmful behaviors.

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