GRADIENT AI HACKATHON

SHIP SINKING PREDICTION MODEL

Helps detect ship sink

DOMAIN: Surveillance and Security Systems

TEAM DETAILS

Team: 53
CodeZip

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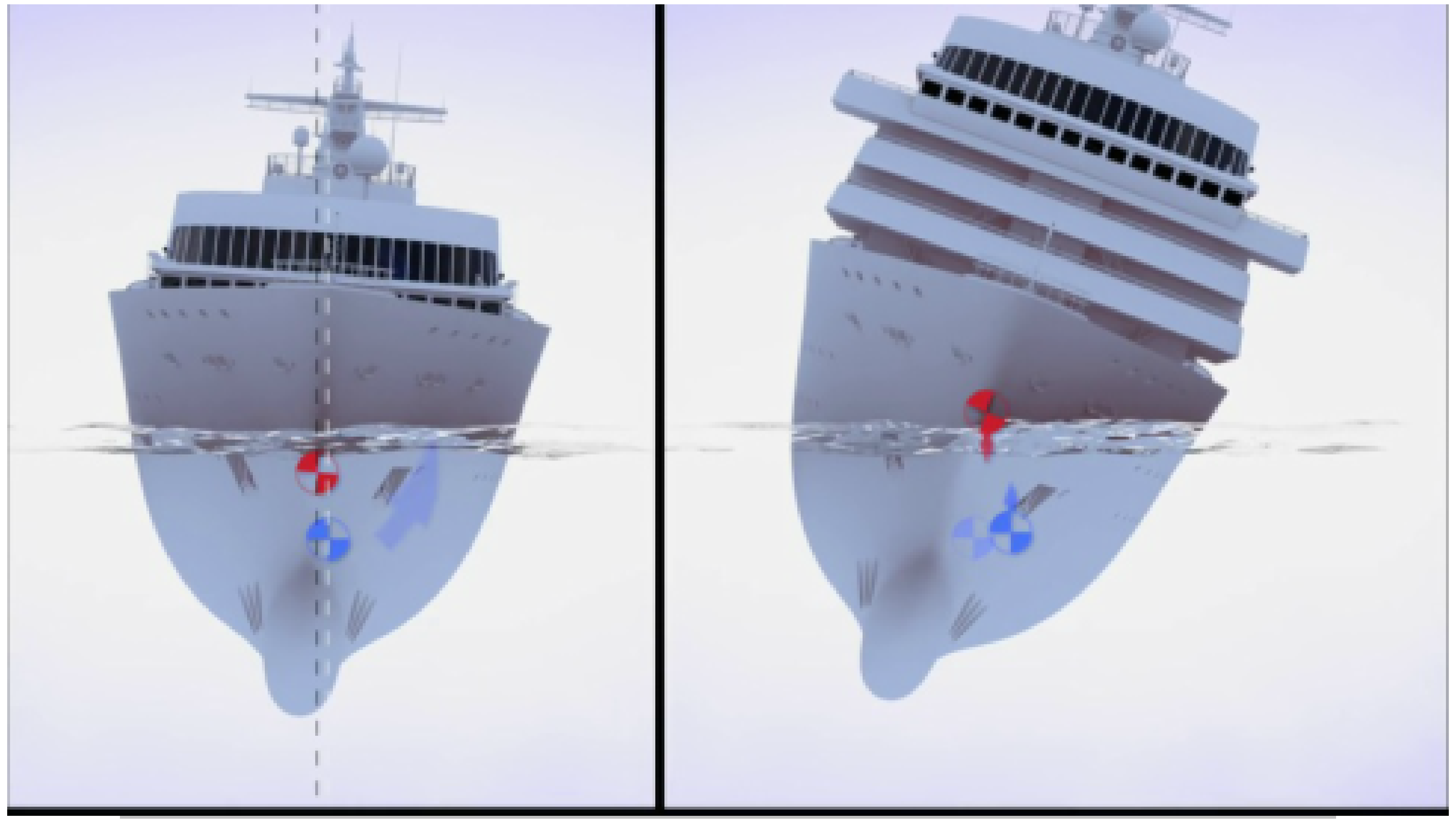
OVERVIEW OF CONCEPT

Shipwrecks have been a significant concern for maritime safety for centuries, and while modern technology has dramatically reduced the number of large-scale incidents, ships still sink each year due to various reasons, including flooding from water leakage.

Currently, there is a lack of accurate, real-time systems to predict sink time after water ingress begins.

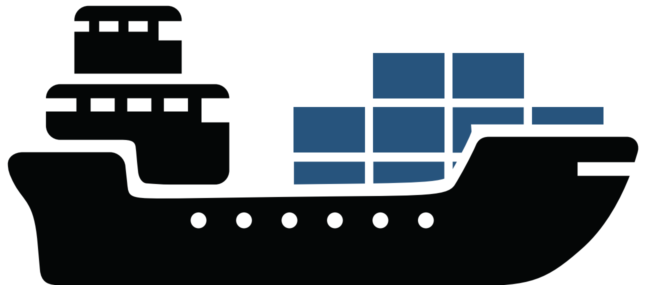
The core objective is to predict the time it will take for a ship to sink once it has started taking on water. This involves analysing the sequence of events that lead to flooding, the ship's stability, and how long it takes for the ship to submerge.



PROBLEM STATEMENT

The maritime industry faces significant challenges in predicting how long a ship can remain afloat after critical incidents like hull breaches or flooding. With over 100 to 200 large ships lost annually due to various causes, and water ingress contributing to 60-70% of these incidents, timely and accurate sink-time predictions are essential for improving safety and reducing losses.
However, current systems lack real-time, data-driven predictions, leading to delays in evacuation, inefficient crisis management, and limited feedback for design improvements.

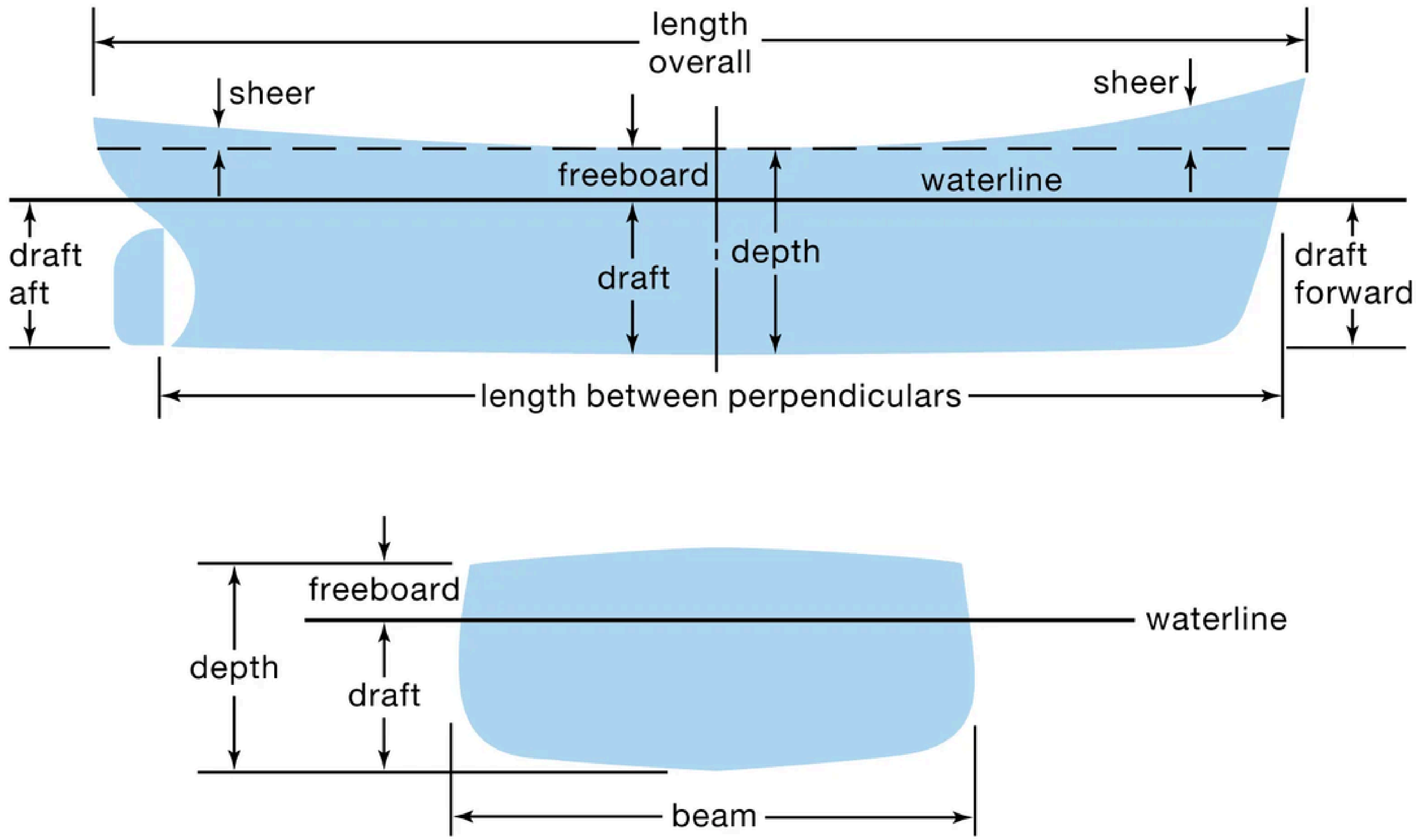
This project aims to develop a deep learning model leveraging ship design, flooding rates, breach locations, and environmental factors to accurately predict sink times. By enhancing emergency protocols, preventative measures, and design optimization, this solution will transform maritime safety, reducing both human and material losses.



OUR APPROACH TO SOLUTION

A Recurrent Neural Network (RNN) model will be trained on historical shipwreck data, including real-time flooding rates, ship specifications, and weather conditions. The model will predict the time to sinking, enabling safer and more efficient maritime operations.

The model will be trained on historical and real-time datasets, including ship specifications, flooding rates, breach locations, and environmental factors like sea state and weather conditions.



OUR APPROACH

Key Components:

1. Data Integration Platform:

    - Collects real-time data from sensors on board ships, including

- water level monitors: to determine whether the hole is above/below draft
- hull integrity sensors: for hole detection, size and rate of expansion based on pressure
- weather conditions: to determine tides, wind to monitor movement of water and ship vigorously

    - Processes historical data on ship sinkings for model training, covering various scenarios such as collisions, structural failures, and severe weather.

2. Predictive Model:

    - The RNN or LSTM model will analyze time-series data to predict sink time dynamically, considering how flooding progresses across compartments and how external conditions impact ship stability.

    - Outputs a real-time countdown to estimated sink time, allowing for immediate action.

OUR APPROACH

3. User Interface for Crew and Rescue Teams:

   - Onboard Dashboard: Displays predictions directly to the ship's crew, providing alerts and recommended actions.
   - Rescue Coordination Interface: Provides remote access for coast guard and rescue teams to prioritize response efforts and allocate resources effectively.

4. Continuous Learning and Updates:

   - The system will incorporate new incident data to continuously improve its accuracy.
   - Feedback loops from real-world deployments will be used to refine predictions and enhance safety measures.

WHAT WE DID SO FAR

1. Collection and preparation of databases

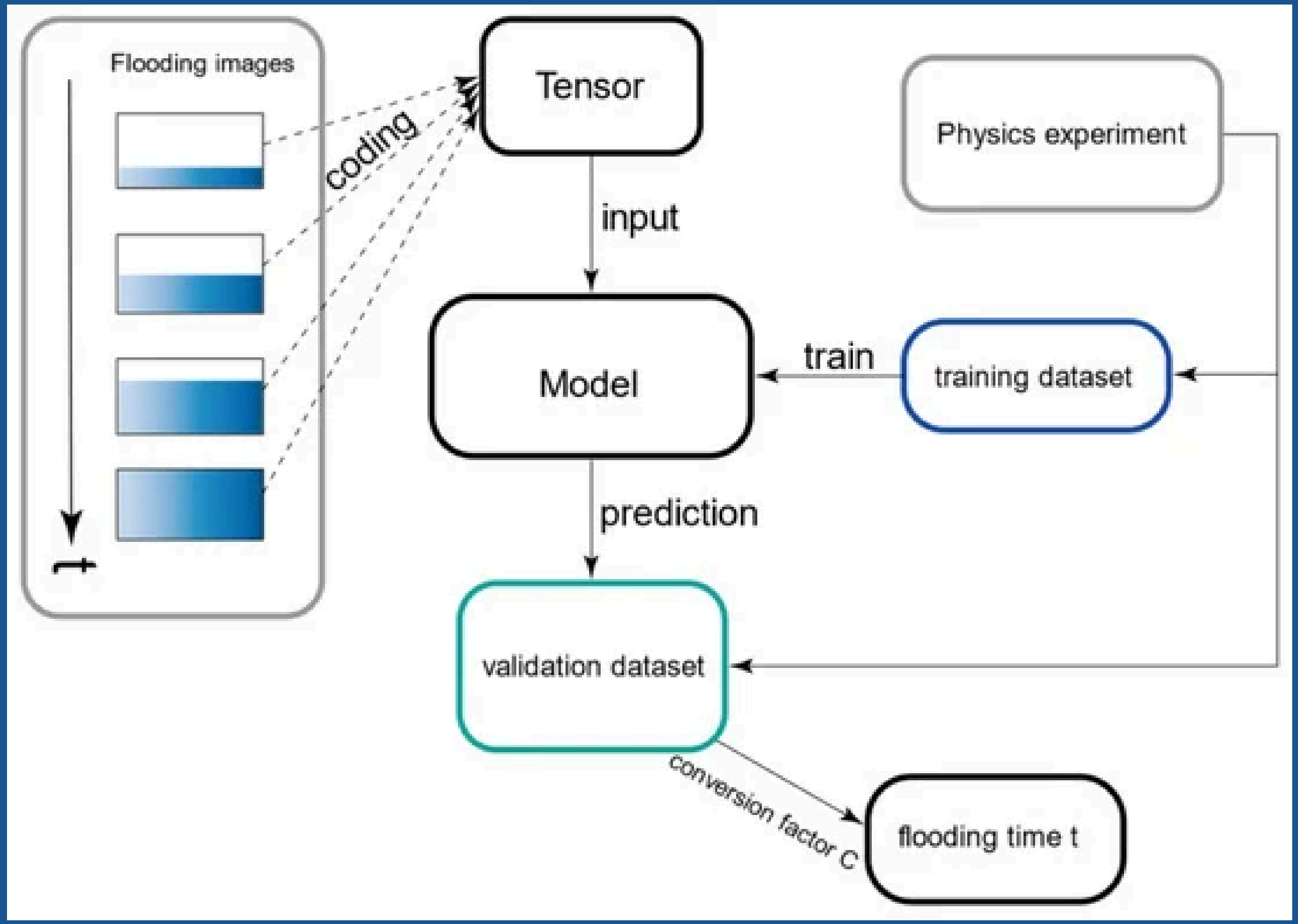
- Kaggle, ReasearchGate:- were used to obtain datasets with details such as: dimensions of the ship, draft length, hole dimensions,etc(as a Q co-ordinate) and time taken to sink(as a X co-ordinate)

Here is a snippet of of one of the datasets used

Company_Name	ship_name	built_year	gt	gt2	dwt	length	width	height	a_lenght	a_area	v_displaced	draught	depth_ofhole	v_ship	Q	time	time in min	y
PRELUDE	Offshore Support Vessel	2017	49.9167	499167	394330	489	74	111	111	5	48732.26541	1.35	1.35	4016646	25.7196423	154275.6189	25.71260316	27
MSC LORETO	Container Ship	2023	23.6184	236184	240000	399	60	90	90	5	23057.97734	0.1	0.1	2154600	7	304506.0032	50.75100054	52
MSC FEBE	Container Ship	2019	23.2618	232618	228149	400	62	93	92	7	22709.83882	0.09	0.91	2306400	29.56288213	77248.56294	12.87476049	14
MSC ARINA	Container Ship	2019	22.8741	228741	228111	400	61	91.5	91	18	22331.33825	0.09	0.41	2232600	51.02611096	43316.42408	7.219404014	8
EVER GOVERN	Container Ship	2019	21.9688	219688	198937	400	59	88.5	88	15	21447.51941	0.09	0.41	2088600	42.52175914	48613.99252	8.102332087	9
MAASTRICHT MAERSK	Container Ship	2019	21.4286	214286	190326	399	59	88.5	88	16	20920.1374	0.09	0.41	2083378.5	45.35654308	45472.12425	7.578687376	9
ONE TREASURE	Container Ship	2018	21.0691	210691	189766	400	58	87	86	3	20569.1677	0.09	0.91	2018400	12.66980663	157684.3981	26.28073302	27
ORE SHENZHEN	Bulk Carrier	2018	20.3953	203953	398997	362	65	97.5	97	17	19911.35577	0.08	0.42	2294175	48.77548565	46627.18606	7.771197676	9
SAHAM MAX	Bulk Carrier	2013	20.1705	201705	400694	360	65	97.5	97	12	19691.88988	0.08	0.42	2281500	34.42975457	65693.41368	10.94890228	12
BARZAN	Container Ship	2015	19.5636	195636	199744	400	59	88.5	88	6	19099.39054	0.08	0.42	2088600	17.21487729	120215.8212	20.0359702	21
MARSTAL MAERSK	Container Ship	2014	19.4849	194849	213971	399	59	88.5	88	18	19022.55795	0.08	0.42	2083378.5	51.64463186	39972.3237	6.66205395	8
MSC DIANA	Container Ship	2016	19.425	194250	202036	400	59	88.5	88	11	18964.07927	0.08	0.42	2088600	31.56060836	65576.55344	10.92942557	12
COSTA TOSCANA	Passenger (Cruise) Ship	2021	18.6364	186364	13000	337	42	63	63	8	18194.19134	0.13	0.13	891702	12.76996476	68403.30612	11.40055102	12

WHAT WE DID SO FAR

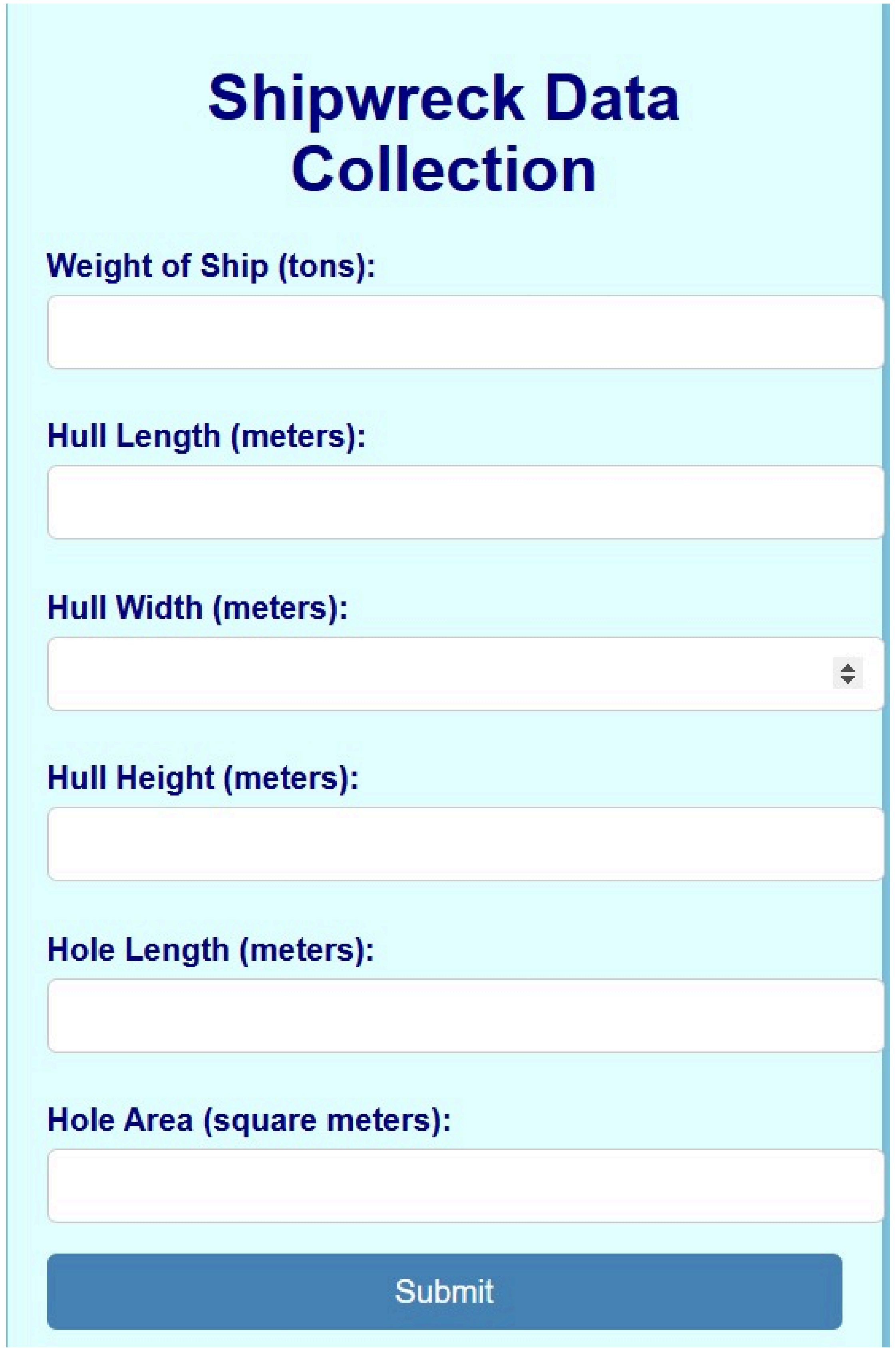
2. Deep learning model
- The data collected, also from maritime accident reports, databases like the IMO, MAIB, and shipwreck archives were gathered and cleaned to check for any missing values.
- We've worked on the architecture of the model
- Data splitting for training



Process sketch of the composite neural network.

WHAT WE DID SO FAR

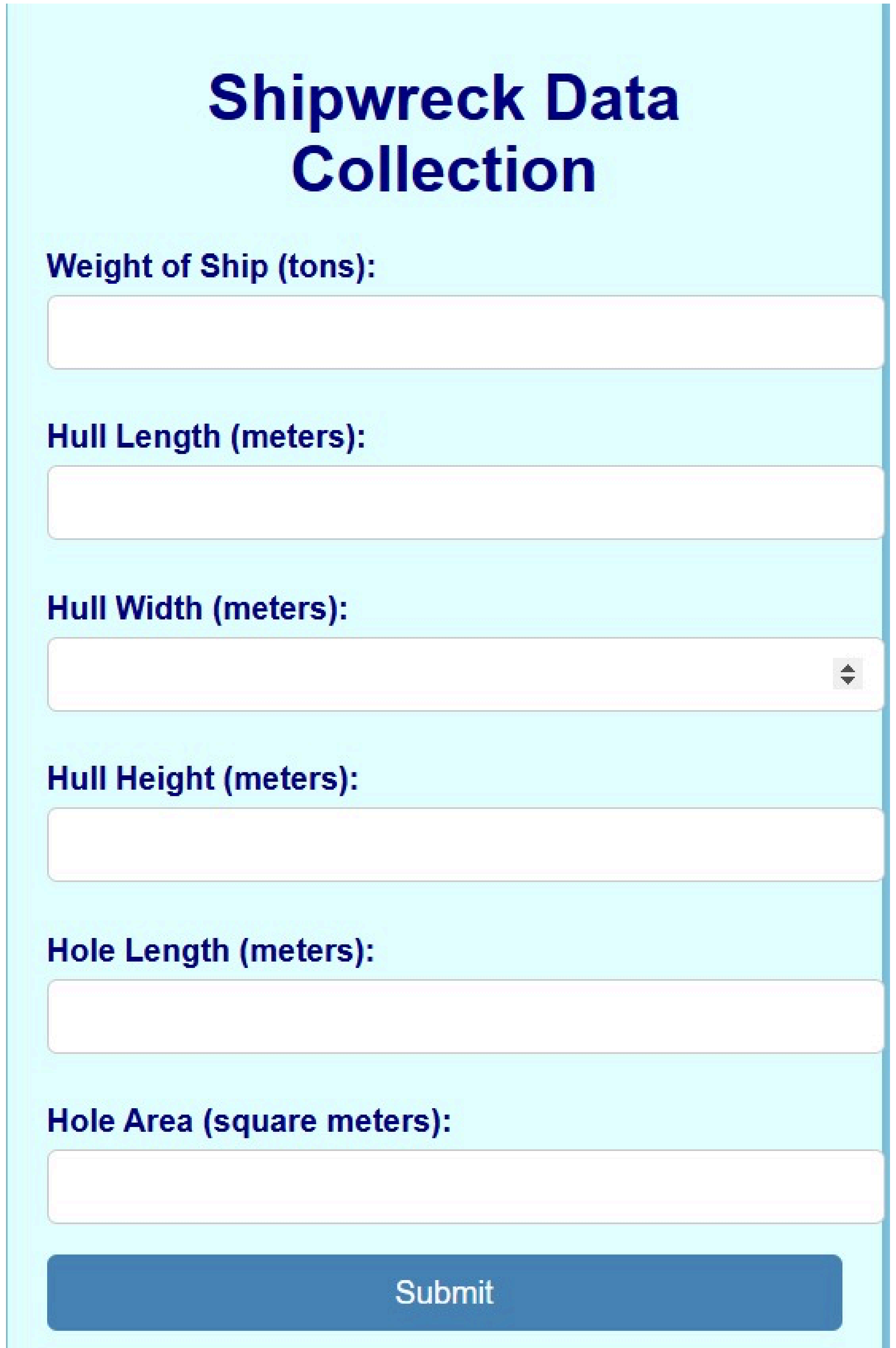
3. User Interface
   - A prototype of website to collect dimensions of ship and hole dimensions to evaluate time
   - (The physical parameters and hole dimensions can also be obtained from inbuilt sensors for real time prediction)



TO BE DONE OVERNIGHT

- complete model training and evaluation
- Integration into a website for user to access

FINAL GUI



When user enters details we can expect an alert