An Insight on Gravity Spy dataset and Machine Learning techniques for Glitch Classification in Gravitational Waves

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Abstract

Gravitational waves are distortions in the space-time continuum produced when heavenly bodies interact. In 1916,as per relativity theory, Albert Einstein hypothesized the presence of gravitational waves. These waves are difficult to detect, yet they contain an abundance of data about the things that generated them. LIGO which stands for ”Laser Interferometer Gravitational-Wave Observatory” discovered gravitational waves for the first time in 2015, begetting more research and analysis. By analysing the gravitational waves released by the earlier objects in the universe, cosmologists can gain insight into the conditions of the universe that prevailed after the Big Bang. These Waves can also be used to study how matter is distributed in Universe and to discover new objects such as dark matter, exoplanets and black holes. The existence of glitches, which are noise transients, affects the processing of GW data. If some glitches excite the detector at the same frequency as gravitational waves, they may impede analysis. In order to recover segments of gravitational wave signals that coincide with a glitch, it is necessary to correctly interpret glitches. Classification of these glitches is also very important as it tells the origin of the glitches and hence help in their removal from the gravitational wave. The recent developments in the disciplines of Data Science and Artificial Intelligence have unveiled new and robust detection and analytical tools. This work includes a survey report on the identification and classification of glitches by different researchers, as well as critical insights and analyses on the topic.This work at its first part explores the dataset - Gravity Spy where we have identifies few issues which may be unknowingly have not been identified in any of the work we have studied for this paper.On the other side, it is demonstrated with illustrations, that methodologies studied thus far may fail when applied to glitches belonging to new classes and new unknown glitch images.

Keywords: Gravitational Waves, Neural Networks, Glitches, Deep Learning, Gravity-Spy, LIGO, VIRGO.

1. Introduction

Machine learning and its various applications have been studied in various areas. These days everywhere artificial intelligence, machine learning and its models, and data analysis are buzzwords. Day by day its applications are increasing. Astronomy is also one such area where machine learning has proved how much complicated data will be there , machine learning with data science can create its magic. Multiple researches have been conducted in astronomical area using machine learning like exoplanets identification , identifying the possibilities of harboring life on different cosmological objects like moon, planets or exoplanets, star- galaxy separation, galaxy classification and identification, supernovae classifications and many more. Gravi- tational wave analysis and study of its parameters is also one such area. This paper explores on a phenomena found in gravitational waves called as Glitches which basically hinders the study of these waves.Glitches are some sort wave having same frequency and somewhat similar characteristics as that of gravitational waves.

Also, glitches are of several types. Some of these types have been explored and many are unknown. Hence, identification that whether glitch is present or not in gravitational wave is a problem and another is which type of glitch is present because, if glitch type is not known we may pass it as a gravitational wave and hence it will create problem in the study of gravitational waves. As of now from Gravity Spy dataset (discussed in detail in further section),according to which 22 types of glitches are known. However, there can be many more.

This paper's primary objective is to present the study of Gravity Spy dataset mostly used for studying various glitches and compare the various machine learning algorithms utilised to date for glitch categorisation. The paper also presents a comparative analysis between these approaches and shows that models explored so far, what they are claiming worked well with previous data but as the dataset is continuously increasing model's performances are going down. Reason for this may be that each time a gravitational wave is encountered there might be some unknown types of glitches that are present and models are unable to identify them and classify them. Hence, this motivated to present this survey.

1.1. Gravitational Waves

Special theory of relativity proposed by Einstein, transformed physics by demonstrating that time and space are not two independent entities, but rather a single entity known as "space-time."The concept of dynamical space-time is now firmly rooted in contemporary physics. One of the important characteristics of dynamical space-time is its radiative nature, or "gravitational radiation" — which will usher in whole new approaches for viewing various astrophysical phenomena. Einstein gave space-time curvature and rendered it dynamic (Albert Einstein, 1922). The resulting theory of gravity is covariant, (AlbertEinstein, 1915) meaning that its physical measurements predictions hold true regardless of the axes used to measure them. Gravity must be causal for it to be consistent with special relativity: Any alteration to a gravitational origin must be conveyed to viewers at the maximum speed of light, c. This suggests the existence of "gravitational radiation." By integrating a time-dependent Newtonian potential with special relativity, as proved by (Abbottet.al., 2016), it is possible to compute with astonishing accuracy a number of the features of gravitational radiation.

When a binary mechanical system emits gravitational waves, the energy loss rate is defined by quadrapole formula that Einstein discovered. Einstein's quadrupole formula:

$$4\pi r^2 e_4{}^r = \frac{16}{5} T^2 \omega^6 \tag{1}$$

T denotes the tensor with respect toquadrupole moment, whose components are components with respect to moment of inertia of the system, $4\pi r^2 e_4{}^r$ is the energy loss rate due to gravitational waves, and $e_4{}^r$ (along the radius) is the energy component of the gravitational field. A binary system comprises two distant entities. They have plane-based and elliptical orbits. By producing radiation, there is an increase in the orbital angular frequency, loss in the energy of the binary system and the distance between the entities decreases. (Weinstein , 2016)

In (Eddington,Stanley , 1922), the author again derived the quadrupole formula proposed by Einstein in 1918 and obtained the following result:

$$4\pi r^2 e_4{}^r = \frac{32}{5} T^2 \omega^6 \tag{2}$$

(Acernese et.al., 2014) observing a discrepancy between his formulas and Einstein's, he attributed it to a mathematical error in one of the investigations. Einstein included the factor 1/2 inadvertently due to a slight calculation error in his 1918 research (Eddington,Stanley , 1922).

The quadrupole formula indicates that it is difficult to generate GWs due to the requirement of massive masses travelling at relativistic speeds. This is a result of the weak gravitational interaction. Astrophysical objects are the only ones big and relativistic enough to generate detectable GWs.

These gravitational waves have been detected almost a centuryafter they were predicted by Einstein. This discovery was made by the Advanced Laser Interferometer Gravitational-Wave Observatory (LIGO)(Aasi et.al., 2015) and the Advanced Virgo detectors (Acernese et.al., 2014). The first GWs from a BBH, GW150914 were discovered by the advanced detectors during their first observing session (O1) for the period September 12, 2015 till January 19, 2016. (Abbott,Benjamin, 2016). The first direct discovery of GWs from a binary neutron star (BNS), GW170817, was made by the advanced detectors during their second observation session (O2)(Abott et.al., 2017). Ten BBHs and one BNS event were reported by the LIGO-VIRGO Collaboration (LVC) before the end of session 2 and were both listed in the first Gravitational-Wave Transient Catalog, GWTC-1 (Roule, 2021). A total of 50 events were included in the second Gravitational-Wave Transient Catalog (GWTC-2)(Abbott R et.al. , 2021), which adds 39 GW events from the first part of the third observing run (O3a).

The Advanced LIGO (Aasi et.al., 2015) and Advanced Virgo (Acernese et.al., 2014) instruments are kilometer-scale laser interferometers. The Virgo detector is situated close to Pisa in Italy, whereas the two LIGO detectors are situated in Hanford, Washington, and Livingston, Louisiana in the United States. Since 2015, when the upgraded generation of interferometers commenced operating, observing periods and commissioning periods have alternated.

When gravitational waves pass through laser interferometers, they are detected as strains. These strains are given as

$$s(t) = \frac{\Delta}{\delta L} \tag{3}$$

, where δL represents the strain change. To better comprehend the source, length is frequently translated into numerical relativity-based waveform. (Agrawal et.al., 2020)

1.2. Physical Properties Of Gravitational Waves

(Agrawal et.al., 2020)Gravitational waves induce the compression and extension of space matter, as well as the slowing and quickening of time around an object. GW possesses polarisation identical to those of light, which are (i) +(plus) and (ii) x(cross) types, respectively. This polarisation is a result of the binary inspiral pair's precession. Gravitational Waves propagates as waves in space-time at the light's speed . Propagation of these waves will takes place iff(Agrawal et.al., 2020)

$$\text{wavelength} \ll R \tag{4}$$

where R represents space-time's Radius of Curvature (ROC) . Some other wave characteristics like dispersion, absorption etc are not of significance in gravitational waves.

1.3. Applications of Gravitational Waves

1.3.1. Black holes merger

Black holes have mighty gravitational pull such that even light also cannot escape them. These black holes are the leftovers of enormous stars. Humans cannot see black holes directly. Scientists have spent years observing the environment to determine the black hole's existence. According to an article cited in Horizon Magazine, gravitational waves permit direct detection of black holes without the requirement for an "intermediate" space-time messenger.

The first detection of GW by LIGO in 2015, was due to the collision of two different black holes. This collision resulted in ripples in space-time.

1.3.2. Neutron star merger

According to an article by Nola Taylor Redd on Neutron stars, these stars made of neutrons are extremely dense and spin very quickly when a big star bursts in a supernova. Rapid fusion results from the spiral motion of two neutron stars creating gravitational vibrations. According to a LIGO Caltech post, the neutron star merger was spotted for the second time on April 25, 2019. The LIGO observatory then discovered gravitational waves generated by the "GW190425" neutron star merger.

1.3.3. Gamma-ray burst

Gamma-ray burst (GRB), a burst of extremely bright light created by the demise of the most powerful star in the universe, may emit light for several months. Seeing GRBs with a telescope does not provide exhaustive information. Gravitational waves are strongly related to the dynamic mobility of an object's mass and its energy, according to an LIGO Scientific Collaboration article. It can detect GRBs differently than light. On 17 August 2017, NASA's Fermi Gamma-ray Space Telescope discovered a brief Gamma-ray Burst (GRB): GRB170817A which was due to an explosion which produced a light pulse of high energy.

1.3.4. Core-Collapse Supernova Explosion

This explosion happens when a massive star dies and this results in production of gravitational waves. (Hensley , 2019). Direct observations with an optical telescope are incapable of entering a star's core, because light emitted from a star's core cannot infiltrate its surrounding materials. Hence, information regarding the cause of the explosion is lacking. Gravitational waves hence gives a way of learning about dynamics of collapsing of core.

Errors from both instruments and environment introduces noise transients, which are called as glitches and this hampers the analysis of GW data. These malfunctions can be triggered by a variety of factors, including earthquakes [(Schwartz et.al., 2020), (Figura et.al., 2022)], lightning strikes [(Valdes G et.al. , 2020), (Washimi et.al. , 2021)], and human activity in the area [(Nguyen et.al., 2021), (Acernese et.al. , 2022)]. Instrumental problems with the detectors themselves may potentially lead to malfunctions [(Accadia T et. al. , 2021)]. If some of these glitches hit detector with the same frequency as binary coalescences, they may interfere with bias analysis [(Pankow et al , 2018), (Powell,, 2018), (Macas Ronaldas et.al., 2022), (Payne Ethan et.al., 2022), (Davis, D et.al., 2022)]. Not only must we be able to discriminate between genuine gravitational-wave occurrences and glitches, but we must also comprehend glitches well enough to recover bits of the gravitational-wave signal that may overlap with the glitch.

In the publication titled "Machine learning for Gravity Spy: Glitch categorization and dataset," (Bahaa- dini et.al., 2018) the Gravity Spy dataset was made publicly available. This collection has 8583 images of LIGO faults and the parameters for 22 error classes. For the conventional test set, the optimal classifier, deep neural network models' ensemble plus an SVM model, obtained an accuracy of 98.21%. However, the glitch classifications observed in LIGO data will change over time.

1.4. Introduction of Existing Machine Learning Techniques Used in Glitch Classification

This section provides an overview of the machine-learning techniques that various scholars have used to date (to the best of our understanding and exploration) to classify gravitational wave glitches. The later section of this paper discusses and shows the results of applying these techniques. Also, the analysis of these results has been done in later section of this paper. Machine Learning techniques used so far are discussed as:

1.4.1. Logistic Regression

Logistic Regression is a machine learning classifier that estimates the probability of occurrence of event based on the given dataset with independent variables. Logistic Regression can be used to classify two classes whereas multinomial logistic regression is used for more than two classes.

Logistic regression solves the problem by learning the patterns from a training set using parameters a weight vector and a bias.

$$y = \sum_{i=1}^{n} w_i x_i + b \tag{5}$$

Equation 5 represents the hypothesis function and sigmoid function (Equation 6) is applied to the hypothesis function which outputs the value between 0 and 1 representing the probabilities. The discrete class "0" or "1" that corresponds to this probability value is subsequently assigned. We choose a threshold value to transfer this probability value to a discrete class. The decision boundary refers to this value as the threshold. Within

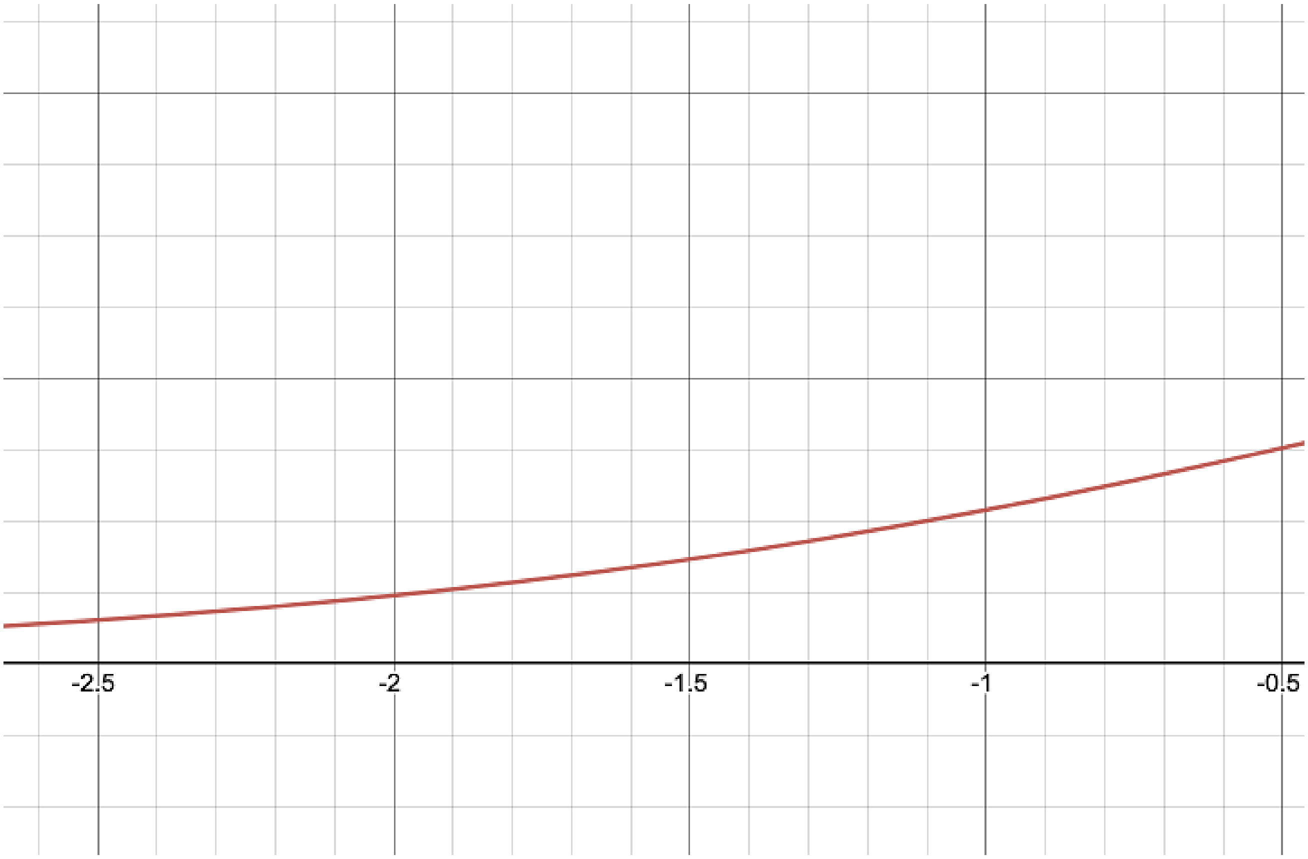

Figure 1: Sigmoid function maps the real values to the range of (0,1)

this threshold value, values will be mapped to class 0, and beyond this threshold value, values will be mapped to class 1.

$$\sigma(y) = \frac{1}{1 + e^{-y}} \tag{6}$$

For example, if we set decision boundary as 0.6 , then probabilities which are greater than equal to 0.6 can be kept in class "1" category else in class "0". However, it makes certain assumptions that must be satisfied like the observations must not depend on one another in order for it to work. It also requires that there should not be any multicollinearity present within the variables.The log odds and linearity of independent variables are presupposed in the logistic regression model. It also needs a huge amount of data to provide good accuracy.

1.4.2. Support Vector Machines

Support Vector Machine comes under supervised machine learning category which is primarily used for classification tasks. A decision-making boundary called hyperplane is used to segregate the n-dimensional space into n-classes.SVM looks for a hyperplane that best distinguishes between two information categories. The information input is viewed as a set of vectors, and the vectors supported are the data points that specify the grading limit. The algorithm creates a decision that is defined by support vectors. In order to guarantee linear (the "kernel trick") and non-linear connections within the information, the input features

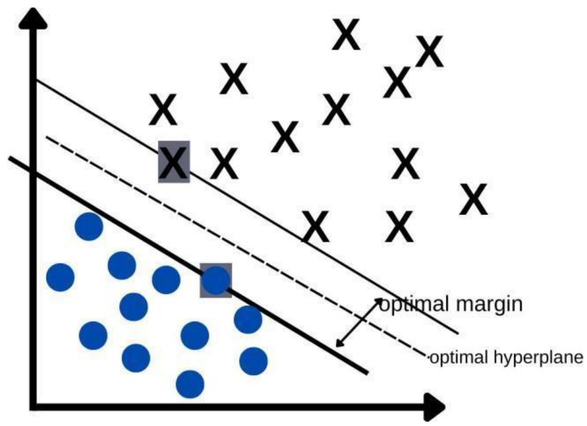

Figure 2: An example of a 2-dimensional space-separable problem. The support vectors, denoted with grey squares, define the separation between the two classes.

are transformed to a greater dimension using the kernel. Linear choice limits are then established in this area. The kernel is a mathematical function that is applied so that the non-linear data points observed in the data set can be transformed into the linear data points such that they can be separated to a large extent. [(Cortes, 1995)]. A hyperplane which is termed an "optimal hyperplane" is a linear decision function with the maximal margin between the vectors of the two classes ((Cortes, 1995)). To create the ideal hyperplanes, a small number of data points referred to as Support Vectors from the training set are considered. These points remain close to the hyperplane and influence its position and orientation. SVM can be used for face detection, text recognition, etc. Two hyperparameters are there in the algorithm— the kernel size and classification error cost— help prevent overfitting. Another variable that can be changed is the kernel form, with the Radial Gaussian base matrix being a common choice. The primary characteristic of radial basis functions is that they exhibit monotonically escalating and descending trends as one moves away from the centre. The centre, distance scale, and radial function shape are the three primary model parameters. The multivariate functions are approximated by these functions using a linear combination of univariate functions. The mathematical illustration that demonstrates how RBF impacts a set of hypotheses, H(x), for any dataset DS(x, y), where data set has N number of points, is shown below.

$$H(x) = \sum_{i=1}^{n} w_i \, exp(-\alpha || \, (x - x_i)^2 ||) \tag{7}$$

Thus, each datapoint in the dataset has an impact on the observation's Gaussian form (bell shaped curve). Impact will be zero if datapoint x $\rightarrow \infty$. There are various types of radial functions, including multiquadratic and thin-plate splines etc.

1.4.3. Convolutional Neural Networks

Convolutional Neural Networks (CNN) is a whole new set of neural architecture known for Image, speech or audio signal inputs introduced in the year 1980 ((Fukushima, 1980)). CNNs proved to have better performance in dealing with image data which is used mainly for feature extractions and reducing the

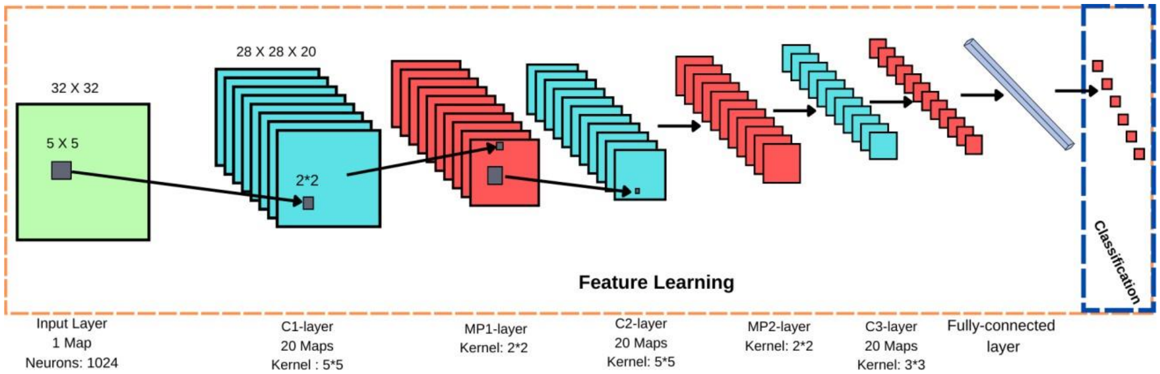

Figure 3: (Courtesy ((Fukushima, 1980))MPCNN architecture using alternating convolutional and max-pooling layers

dimension of images. Model has 3 primary layers : Convolutional, Pooling and Fully-connected (FC) layer. CNN increases in its complexity which is used to extract the important patterns in the image. The initial layers of CNN focus on simpler features like edges, colours, etc whereas the deeper layers focus on complex features like size, shapes, etc. Figure 3 represents the CNN architecture for the classification of 6 classes. The convolution layer is the core component of CNN architecture where most of the computation happens. It needs very less components, mainly input data, a filter, and a feature map. Filter or Kernel detects the feature. It is a two-dimensional weighted array that scans all the receptive pixels of the image, and judge if the feature is present in that receptive pixels or not. This is called as convolution.

Pooling Layer is next to the convolutional layer to de-sample the outputs of convolutional layers by sliding the filter of n x n size with some stride size and calculating the maximum(MaxPooling) or average(Average Pooling) of the input.

1.4.4. Transfer Learning

CNNs undoubtedly able to extract the features from the image data but take much time to learn features with complex architectures. A new learning method called Transfer Learning focuses on applying the knowledge to other related problems without re-training the model from scratch. This method proven to learn the features in comparatively less time than traditional CNNs which are built from scratch. This is a popular deep learning approach used as an inceptive point for computer vision and deep learning problems. Inductive Transfer is the form of transfer learning used in deep learning. Transfer learning models use pre-trained models. These pre-trained models saves time for making models to train or learn as these are trained on some other but similar task.

Transfer learning can be further divided intohomogeneous andheterogeneous transfer learning based on the disparity between areas ((Weiss et.al., 2016)). For cases where feature space is almost same, homogeneous learning approaches are created and put forth. When the fields have different feature spaces, the knowledge transfer process is called as heterogeneous transfer learning ((Zhuang et al , 2020)).

Two general approaches for transfer learning are Develop Model and Pre-trained model approach. In first approach, following four steps are followed: Choosing the source task, developing the source model, reusing the model and fine tuning it. Whereas in the Pre-trained model, three steps need to follow: Selecting the pre-

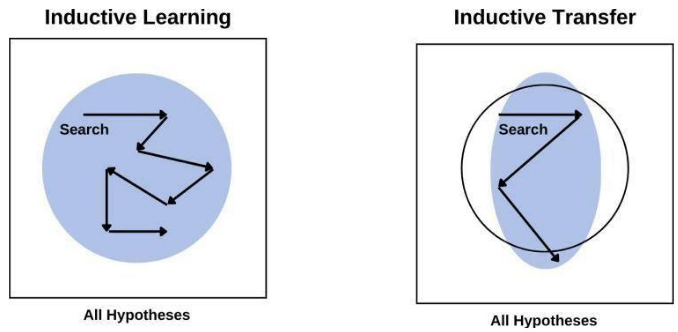

Figure 4: (CourtesyHe Kaiming et.al., 2016) Inductive Transfer Illustration from Transfer Learning

trained model which is released by many research institutions, Reusing the model and Tuning the model. Some of the pre-trained models are ResNet ((He Kaiming et.al., 2016)), VGG((Simonyan and Andrew, 2014)), InceptionNet ((Szegedy et.al., 2015)), etc.

1.4.5. Ensemble Learning

Ensemble Learning is a machine learning technique that is used to improve accuracy by combining various machine learning algorithms. This algorithm allows machines to learn various features compared to a single model. Ensemble learning is of three types: Boosting, Stacking and Bagging.

Bagging in general is an ensemble learning technique that seeks out a diverse collection of basic models called as ensemble candidates by changing the training data. By combining different model types that are fitted to the training data and combining predictions using a model, the ensemble technique is known as stacking that targets a diverse group of members. In order to highlight situations when previously fit models on the training dataset exhibit mismatch, an ensemble technique called "boosting" seeks to change the training data.

2. Data Source

Gravitational wave signal GW151226 due to the coalescing of two stellar-mass black hole binary sys- tems was detected by Advanced LIGO detectors on 14th September 2015 (Abbott,Benjamin, 2016). The Gravitational-wave data generally comprises transient noise along with the actual signal wave. Time- frequency spectrograms are generally used to visualize the data along with this transient noise (Bahaadini et.al., 2018). Time-frequency morphology is a type of signal processing technique used to analyze non- stationary signals. It involves the analysis of the frequency content of a signal over time, which can be used to identify patterns, trends, and other characteristics that may not be visible when the signal is considered as a whole. Time-frequency morphology can also be used to extract information from non-stationary signals, such as speech or audio signals. In the Gravity Spy dataset, the images are a type of spectrograms which are obtained from the process called Q-transforms which transforms data series to the frequency domain. The standard dataset meets quality standards, while the Gravity Spy dataset has Q-transformed images for the transients detected by the detector's gravitational-wave channels that are louder than a particular thresh- old, specifically the signal-to-noise ratio (SNR) (Abbott et. al., 2016). The Gravity Spy dataset consists of 22 different morphological glitch classes which were selected (the larger LIGO Scientific Collaboration had already identified the names and morphology of several of these classes and hand selected tens to hundred of these example images (often with input from algorithms, such as the Hierarchical Veto (Smith et.al, 2011) that categorise glitches according to how they relate to other forms of disturbances, such as seismic noise).

These categories are also the classification options (buttons) that users of the Gravity Spy project interface must select.

Gravity Spy consists of 7,966 spectrogram images of 22 different classes categorised into the train, test and validation directories.

Works carried out by ((Yan et.al., 2022)), used the Gravity Spy dataset which consists of 7,996 spec- trogram images of 22 classes categorized into training, testing and validation directories. The results of numerous studies and analyses of the works conducted with Gravity Spy are discussed in detail in the subse- quent sections. However, the recent release of Gravity Spy has 31,868 images and several unexplored classes. The existing models must continue to be tested on the new dataset to determine whether they are still applicable to the new dataset with the same accuracy.

Directory	**Number of Images**
Validation	1,200
Test	1,179
Train	5,587

The below represented 22 classes are listed in the gravity spy dataset. Due to the change in weather and geographic conditions at the LIGO detector, classes are neither exhaustive nor static. There are many pos- sible sub classes of glitches, and sometimes there are new or short-lived classes of glitches (Bahaadini et.al., 2018). These 22 classes are an attempt to delineate the most representative and distinguishable classes during LIGO’s first and second observing runs from September 2015 to December 2015 (O1) and November 2016 to August 2017 (O2), respectively, (Bahaadini et.al., 2018).

Glitch Type	**Number of Images**
1080Lines	328
1400Ripples	81
Air Compressor	58
Blip	1,821
Chirp	60
Extremely Loud	447
Helix	279
Koi Fish	706
Light Modulation	512
Low Frequency Burst	621
Low Frequency Lines	447
No Glitch	150
None of the Above	81
Paired Doves	27
Power Line	449
Repeating Blips	263
Scattered Light	443
Scratchy	337
Tomte	103
Violin Mode	412
Wandering Line	42
Whistle	299

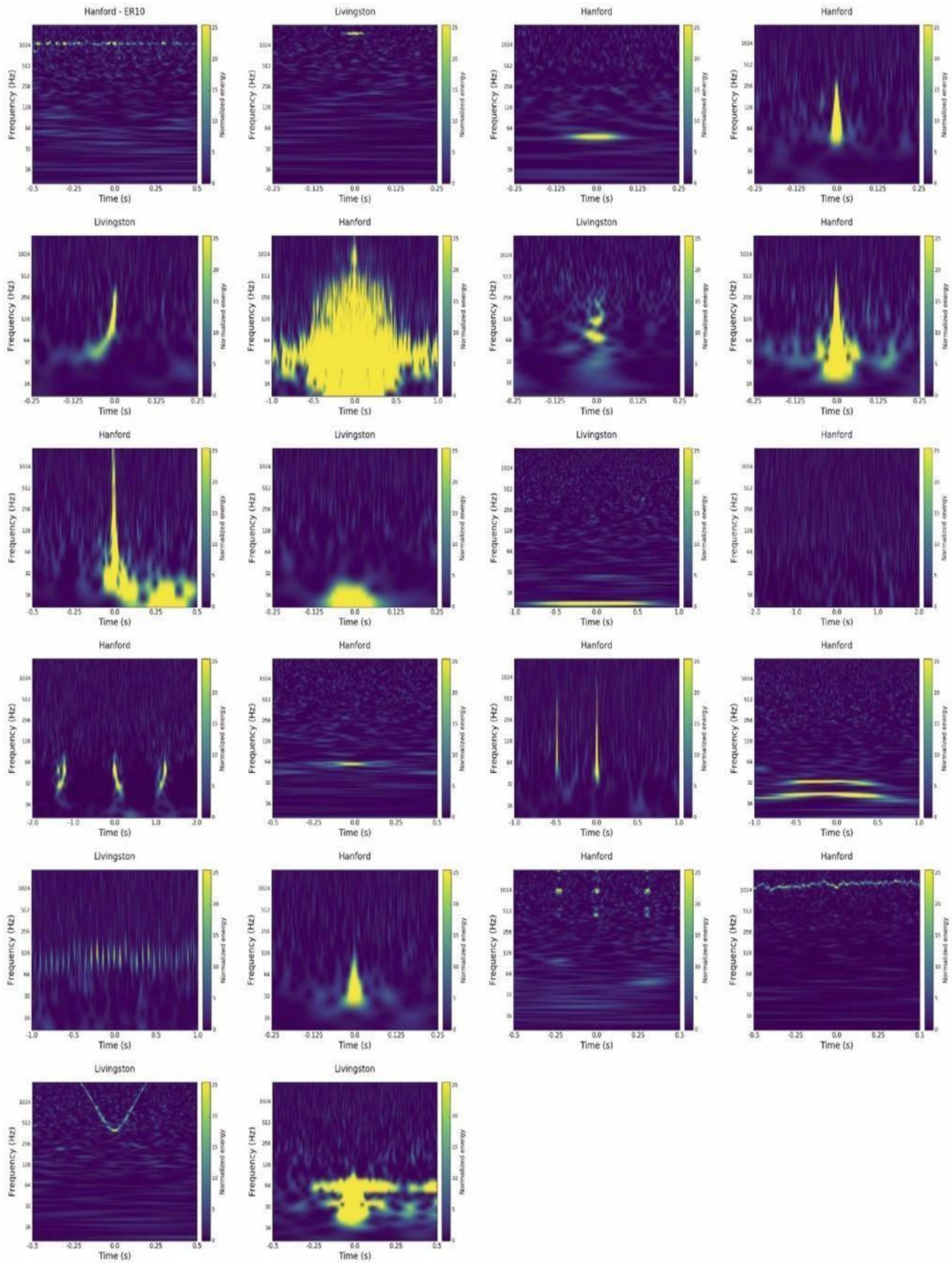

Figure 5: Omega Scan images for example members of each class within the Gravity Spy dataset. From top left to bottom right; row one: 1080 Lines, 1400Ripples, Air Compressor, Blip, row two: Chirp, Extremely Loud, Helix, Koi Fish, row three: Light Modulation, Low Frequency Burst, Low Frequency Lines, No Glitch, row four: Paired Doves, Power Line, Repeating Blips, Scattered Light, row five: Scratchy, Tomte, Violin Mode, Wandering Line; row six: Whistle, None of the Above (one possible example, this class can have various forms) (Coutesy:Bahaadini et.al., 2018)

Class	Total	Train Set	Valid Set	Test Set	Duration	Frequency	Evolving
1080Lines	328	230	49	49	Long	High	No
1400Ripples	232	162	35	35	Short	High	No
Air Compressor	58	41	8	9	Short	Low	No
Blip	1869	1308	281	280	Short	Mid	Yes
Chirp	66	46	10	10	Short	Mid, Low	Yes
Extremely Loud	454	318	68	68	Long	High, Mid, Low	Yes
Helix	279	195	42	42	Short	Mid, Low	Yes
Koi Fish	830	581	125	124	Short	Mid, Low	Yes
Light Modulation	573	401	86	86	Long	Mid, Low	Yes
Low Frequency Burst	657	460	99	98	Short	Low	Yes
Low Frequency Lines	453	317	68	68	Long	Low	No
No Glitch	181	127	27	27	Long	-	No
None of the Above	88	62	13	13	Short	High, Mid,Low	Yes
Paired Doves	27	19	4	4	Short	Mid,Low	Yes
Power Line	453	317	68	68	Short	Low	No
Repeating Blips	285	200	69	42	Short	Mid	No

Scattered Light	459	321	69	69	Long	Low	Yes
Scratchy	354	248	53	53	Long	High, Mid	Yes
Tomte	116	81	17	18	Short	Low	Yes
Violin Mode	472	330	71	71	Short	High	No
Wandering Line	44	31	6	7	Long	High	Yes
Whistle	305	213	46	46	Short	High	Yes

Among all classes, there is a class labelled as "None of the Above" which signifies that all 81 spectrogram images in this class does not fit into any other glitch class and remain unclassified. All 150 images of the "No Glitch" class signify no glitch is detected at the LIGO detector.(Bahaadini et.al., 2018) Each Image in the gravity spy dataset is 570 x 470 pixels

There was a noteworthy observation that we have made in Gravity Spy dataset. The trends we have observed Bahaadini et.al. that may have an impact on model's precision. The literature that we have explored for this research have no where mentioned about these observations. There are 137 spectrogram images in the dataset which are categorised as glitches despite not having any glitch data i.e. we observed empty spectrogram here as shown below in Fig:6 an illustration from the dataset. In this particular spectrogram as can be seen the glitch falls under the category Whistle , where there is no glitch in actual. The literature studied so far on Gravity Spy dataset as per best of our knowledge have nowhere

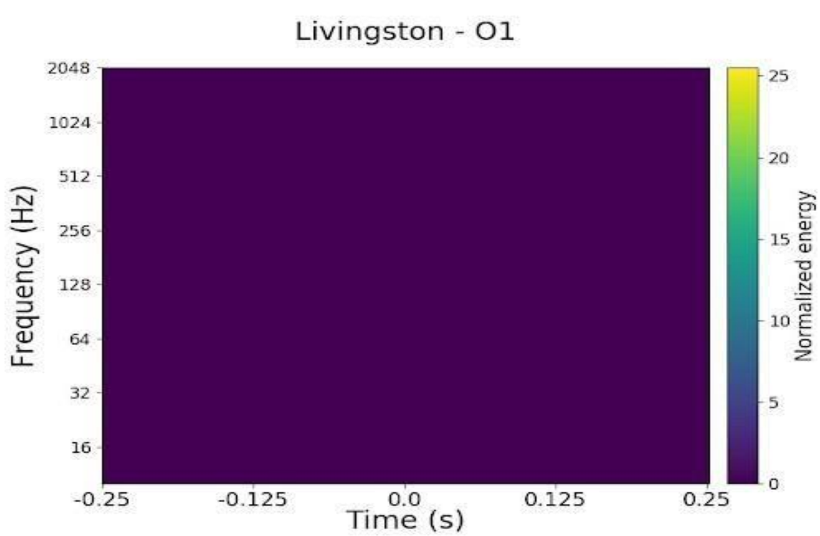

Figure 6: Empty Spectogram Image classified as Whistle from Livingstone observatory in O1 run

mentioned about empty spectrograms being given as a glitch class. It should have been categorised in dataset however as NoGlitch class but has been categorised into another glitch category. Another important observation which we have made on this dataset was that the glitches classified under same cate- gory have different spectrograms. Although they belong to the same class, the glitch images are radically distinct in appearance. Despite coming from the same class, the glitches from Livingston and Hanford observatories look distinct. As can be observed from Fig:7 Glitch (from Hanford) categorised as Whistle has different spectrogram as compared to spectrogram obtained from Livingston. Again the literature work explored have nowhere any mentions about these issues with respect to the dataset. For further study , identification and classification of glitches a careful investigation of the dataset is required.

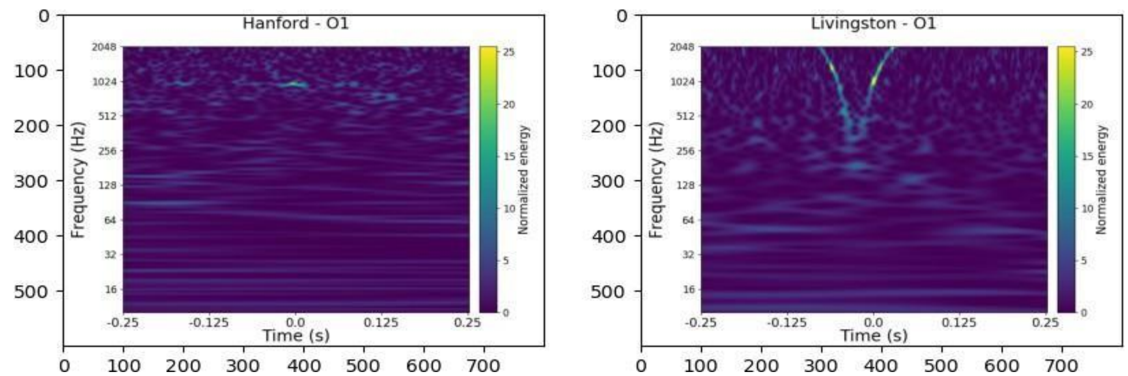

Figure 7: Spectogram Images from Whistle class looking different from Hanford and Livingston O1 runs

Class	Total number of Images	Train Set	Valid Set	Test Set	Total Num- ber of Empty Images	Empty Images in Train Set	Empty Images in Valid Set	Empty Images in Test Set
Blip	1869	1308	281	280	2	2	0	0
Extremely Loud	454	318	68	10	111	78	16	17
Koi Fish	830	581	125	124	2	2	0	0
Low Fre- quency Burst	453	317	68	68	2	2	0	0
No Glitch	181	127	27	27	9	7	1	1
None of the Above	88	62	13	13	2	2	0	0
Paired Doves	27	19	4	4	8	5	1	2
Whistle	305	213	46	46	1	1	0	0

3. Related Work

Several works are being carried out by many computer scientists to detect the glitches in gravitational waves. Among these, one of the notable works is carried out in (Bahaadini et.al., 2018). In this paper, the authors analysed the accuracy of different machine learning algorithms. The linear Support Vector Machine (SVM) Machine Learning Algorithm is implemented using the sci-kit-learn library with 0.1 as the value of Capacity constant (C).

With N data points in training set $x_i{}^N_{i=1}$ and training labels $y \in \{1, -1\}$, the optimization problem solved by SVM is -

$$min_{w,b} \frac{1}{2}||v^2|| + C\sum_{i=1}^{n}\eta_i \tag{8}$$

subject to $y_i(v^T x_i + b) \geq (1 - \eta_i)$ and $\eta_i \geq 0$, for i = 1..n

b and v indicates the parameters of hyperplane (here, v is a coefficients' vector and b is a constant), C is the capacity constant, and also it is a slack variable that deals with interlinked inputs thus enabling approximated solutions if feasible solution doesn't exist. Grid search and n-fold cross-validation are used to perform the hyperparameter's fine tuning (Bahaadini et.al., 2018). By fitting the training and testing data to the Linear SVM model an accuracy of 96.19 % was achieved where value of C was considered as 0.1.

Another algorithm, Kernel Support Vector Machine (SVM) Learning Algorithm was used with a combination of Radial Basis Function (RBF) as the kernel in order to capture non-linearity patterns that exists in Gravity Spy data. The kernel trick is used so that samples can be linearly separated by projecting them intoa different feature space.[(Amari Shun-ichi et.al., 1999), (JC et.al. , 1998), (Watt et.al., 2020)]. The RBF kernel function is as follows (as given in previous section part of equation 7, multiplied with weights)

$$K(xi.xj)= \exp^{(-\alpha||(xi-xj||^2)} \tag{9}$$

The optimal values of hyperparameters of the RBF classifier are C = 5.65 and α = 4e−5 were determined with the help of grid-search technique along with n-fold cross-validation which resulted in 97.12% accuracy. Another approach used by authors was Deep Convolutional Neural Networks (DeepCNNs). It had max pooling and convolutional layers, after which fully connected and softmax layers were implemented using Keras and Theano libraries in Python. A CNN model with an input image size of 280 x 340, convolutional layers with a regularization parameter to r = 2(1e − 4) for L2 regularization and 'glorot uniform' as an initialiser. The Adamax has used an optimiser with the default parameters of Keras2 and other parameters. Its batch size was selected as 30 whereas epochs were specified as 200. This Deep CNN model resulted in achieving an accuracy of 97.67 %.

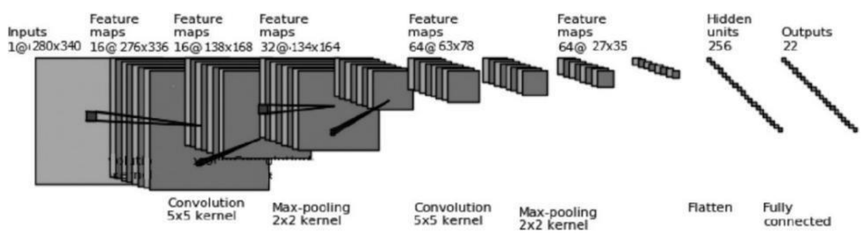

Figure 8: The merged-view model's architecture was optimised for this Gravity Spy dataset.(Bahaadini et.al., 2018)

Another optimal approach, the Ensemble Machine Learning Algorithm framework is used to get the power of various classifiers in a single model. Soft Fusion is a type of the ensemble model used to classify gravitational wave glitches which are stacking with the probabilistic distribution of basic classifiers and the resulting feature vectors were merged to give a single input feature vector to the final classifier. In soft fusion, Linear SVM has been used as an ultimate meta classifier which takes feature vectors of various basic classifiers as input. By this method, the model achieved 98.06 % accuracy. Hard Fusion is another type of ensemble framework used to classify gravitational glitches which do not train the new classifier but perform the weighted summation of outputs of all basic classifiers.

$$p^t_{hard} = w_1 p_{mv_1}{}^t + w_2 p_{mv_2}{}^t + w_3 p_{mv_3}{}^t + (1-(w_1+w_2+w_3))p^t_{svm} \tag{10}$$

The ultimate Ensemble algorithm of hard fusion was able to achieve the accuracy of 98.21 %, which was best among methods used. Another work was carried out using Logistic Regression with elastic net regularisation to identify glitches in LIGO data using only auxiliary channel data. This system achieved around 83.18 % accuracy (Colgan, 2020). Various ML and Deep Learning models can be used to enhance accuracy.

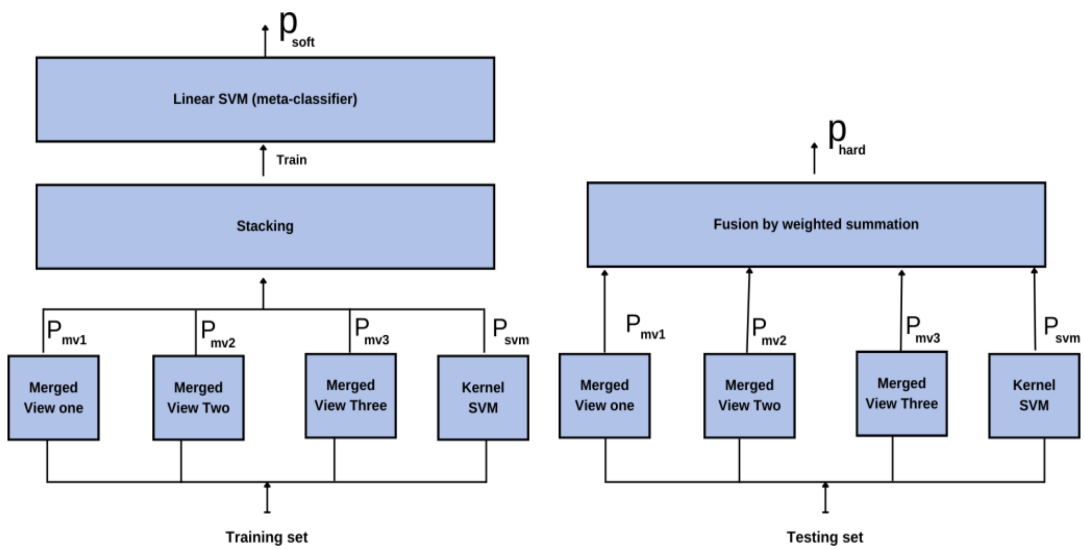

Figure 9: (Courtesy Colgan, 2020)The Ensemble model's architecture fine tuned for Gravity Spy's another version.

Another work carried out in (Colgan, 2020) in the year 2017, used the concept of transfer learning for the classification and also used unsupervised clustering for grouping together anomalies and new types glitches (Colgan, 2020). Gravity Spy is chosen as the data source for the work. Various transfer learning architectures are like ResNet, InceptionNet, and VGG. In analysing the work carried out by other researchers, the model tends to reach accuracies around 97 % but it is not applicable for all classes to be classified at the same level of accuracy. Utilizing state-of-the-art CNNs that have already been trained for object identification, the Deep Transfer Learning technique for glitch classification is used to solve this issue. Authors retrained the algorithm with a small dataset of spectrograms from LIGO and it accurately classified the glitches (Colgan, 2020). With 8 out of 22 classes, this methodology gets a perfect precision-recall rate of 98.8%. Inception models V2 and V3 both got the accuracy over 98% in less than 10 iterations while training whereas VGG models(16 and 19) achieved accuracy above 98% in less than 30 iterations while training.(Colgan, 2020). Trained CNN models could have been used as good feature extractors in order to extract the features and find the new categories of glitches using unsupervised and semi-supervised techniques. For any of the CNN models, eliminating the softmax and fully-connected dense layer close to the output gives a CNN model that converts whatever input image to a vector of real numbers that encodes useful information for classifying various types of glitches.(Colgan, 2020). Hence, whenever some unknown type of glitches appears, which is classified as None of the Above by the CNN model, it can be transformed to vectors using these truncated CNN feature extractors and novel classes or clusters can be found. This work claims the model can be used for the new time-series data of Gravity Spy as well as KARGA (Eiichi et.al., 2014)and LIGO-India(Unnikrishnan,, 2013)data.

Another work carried out in (Yan et.al., 2022) used the concept of Progressive Generative Adversarial Networks (ProGANs) for Image augmentation and transfer learning for classification. Table 1 shows that the spectrogram image distribution is not uniform with all classes. A class labelled 'Blip' contains 1821 images which is 22.86 % of the whole dataset whereas a class labelled 'Paired Doves' contains 27 images which are 0.34 % of the whole dataset. Due to the nature of spectrogram classification, traditional image augmentation techniques are inapplicable for small sample sizes. To address this, the authors propose a variant of Generative Adversarial Networks (GANs) called

Progressive GANs, which can produce very good resolution spectrograms which are almost similar to the quality of the original images and also gives desirable diversity. To begin, authors used the ProGAN framework, which was based on TensorFlow, in order to produce fake images for classes using a smaller training dataset. The original 566 x 466 pixel image was downscaled to a more manageable 512 x 512 using ProGAN. Minibatch sizes tend to get smaller as resolution increases beyond 32×32. The generator's learning rates can be changed on the fly. The generator had a learning rate of $1.5 * 10 - 3$ if the resolution reaches 256x256. After ProGAN was fully trained, the generator had a learning rate of $3 * 10 - 3$. Spectrograms for 20 of the 21 classes (not including None of the Above) may be obtained using the same method and the same parameters for ProGAN. After comparing their generated images to real-world examples of Gravity Spy, the authors claimed that ProGAN's generated images get back the training data distribution properly, and simultaneously also increased the diversity of spectrograms, which is very imortant for achieving less overfits and better generalisation (Yan et.al., 2022). The dataset with a generated set of images is inputted into Deep Convolutional Transfer Learning Networks which are trained by PyTorch on the ImageNet dataset. The output layer contains 21 nodes which represent 21 classes of glitches excluding None of the above. This work uses transfer learning architectures like ResNet50, ResNet101 and InceptionNet-V3 to build the classification models. 299 x 299 taken as input dimension for IncpetionNet-V3 and 244 x 244 image resolution images are taken as input for ResNet50 and ResNet101 architectures. To prevent the model from overfitting or losing the best weights, early stopping methods are used with L2-regularisation. On comparing the metrics of the three models, 99.35 % accuracy is achieved on the test dataset of the ResNet101 model outperforming all models on the test data set whereas the accuracy of 98.43 % is achieved using InceptionNet-V3 which outperforms all models on the training dataset.

It is indicated in the report that the resolution of the original photos has been scaled, however, the data loss is not identified. Similarly, they have not compared the accuracy of various algorithms with respect to models on fake images(GAN-generated images) in this work. There is no evaluation of the model's performance on these fake images. Similarly, there is no study of the model's performance if unidentified glitches emerge. In addition, the model fails to recognise whether a new glitch (outside of the 22 classes) is discovered. This paves the way for more research opportunities involving the detection of glitches of new types or glitches that are subtypes of the 22 classes.

The work carried out in (Glanzer et.al., 2022), classified 379805 glitches from LIGO Livingston and 233981 glitches from LIGO Hanford into semantic classes (Glanzer et.al., 2022). This work also focuses on finding out the glitch distribution and its comparison at two sites LIGO Hanford and LIGO Livingston.

The work carried out in (Coughlin et.al., 2019) used the concept of transfer learning to classify the glitches in gravitational waves. Despite the fact that classification of glitches using machine learning techniques has showed promise, these techniques have a number of limitations. First, supervised machine learning methods, in which a training set of already identified classes of transients is provided to the algorithm, have no quick way to identify further classes present in the data. Unsupervised ML techniques have the drawback they separates the know-how of relationship of classes with the detector from its analysis. Furthermore, as there is overlapping among the clusters and the algorithm learns the attributes from unlabeled data that is not sufficiently discriminatory, unsupervised techniques are hampered by the need that it should only confirm the classes which it has identified. None of the techniques whether it is supervised or unsupervised is ideal though they have their own advantages. The inclusion of None of the above class while classifying is not an effective method for extracting features and classifying with new data. The spectrograms of the recognised Gravity Spy classes are comparable to and different from the unlabeled Gravity Spy glitches due to transfer learning, which tends to provide a better fit in clustering and aids in the discovery of new glitches. A model is developed to find the similarities and dissimilarities of known images of Gravity Spy. For this analysis, DIRECT (Bahaadini et.al., 2018), a transfer learning model is used to find the similarity between the images of the gravity spy. To determine the optimal configuration (setting and training) for DIRECT, two activation functions were tried, tanh and leakyReLU, for fully connected layer which DIRECT extends to the VGG16 model. Moreover,authors tuned the count of training rounds along with the number of pairs having similar and different images randomly selected every time from the training data. Author compared DIRECT to other simpler approaches with raw pixel data for determining similar images (Bahaadini et.al., 2018) and they concluded that DIRECT results are better or comparable based on the glitch.

4. Comparative Analysis

The authors of the research (Colgan, 2020) employed Logistic Regression with elastic net regularisation and attained an accuracy of 83.18 percent using this method. This methodology has the advantage of

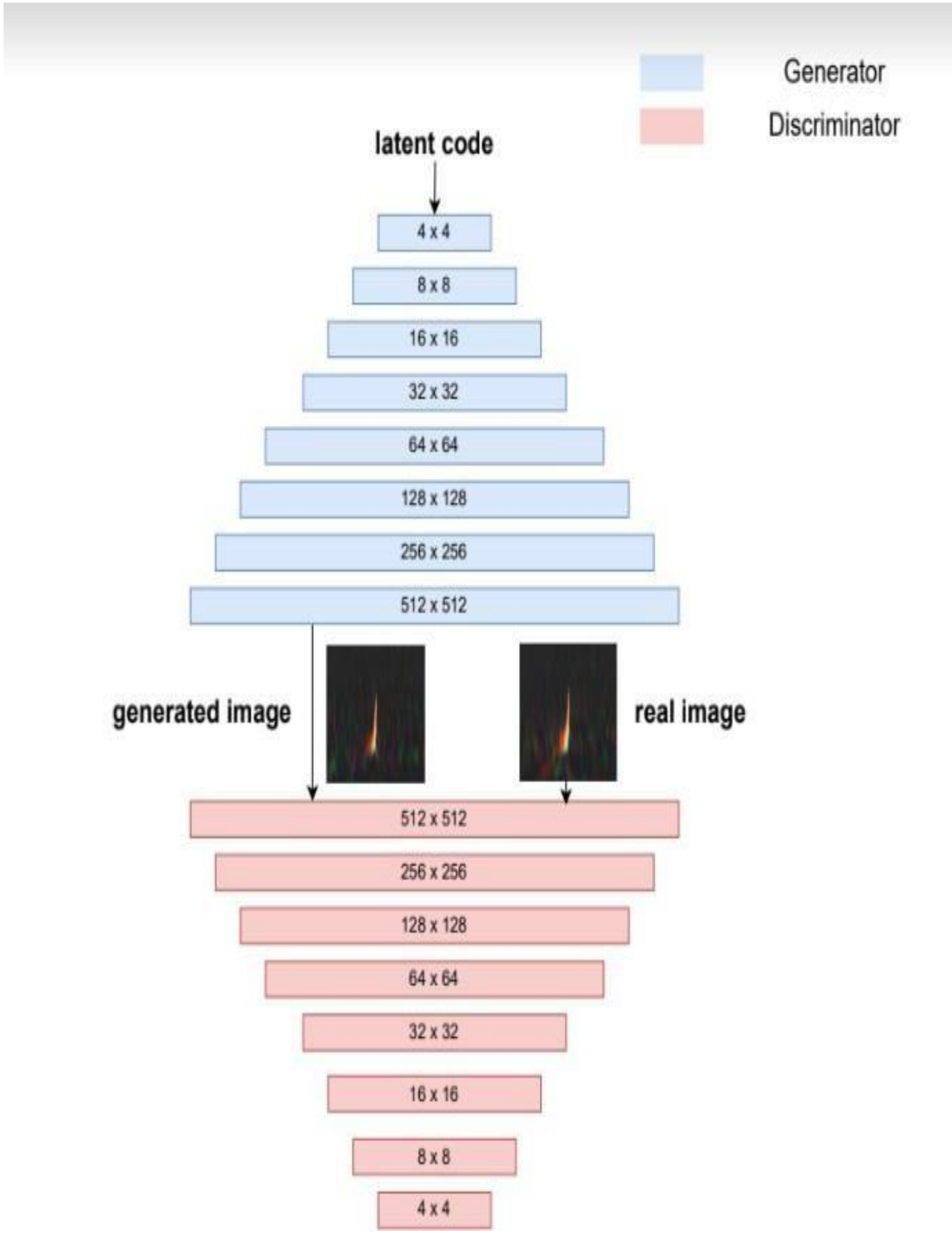

Figure 10: (Colgan, 2020) Graphical representation of the ProGAN generator and discriminator. The first layer of ProGAN's network design provides low-resolution (4 x 4) images, and the second layer adds support for higher-resolution (4 x 4 to 8 x 8) output. It's a recursive process. Growth of the generator and discriminators is always in lockstep with one another.

identifying potentially glitchy LIGO data segments using only auxiliary channel information. However, machine learning and deep learning methods can be utilised to optimise the model.

The authors of the research (Bahaadini et.al., 2018) employed the Hard Fusion method. Hard Fusion is a type of ensemble framework used to classify gravitational glitches that executes the weighted sum of the outputs of the basic classifiers rather than training a new classifier. This work has an accuracy rate of 98.06%. This method has the advantage of precisely identifying the 22 bug classes. But it is unreliable in predicting and identifying new data on glitches.

In the publication (Shen et.al, 2018), unsupervised and semi-supervised Transfer Learning methods were employed. This was able to attain 98.8% overall accuracy and flawless precision-recall in eight out of twenty- two classes. This research states that the model is applicable to the new Gravity Spy time-series data as well as KARGA (Eiichi et.al., 2014) and LIGO-India (Unnikrishnan,, 2013)data. Yet, only eight of the twenty-two classes attain precision recall.

In the paper (Yan et.al., 2022) ProGAN with transfer learning approach was utilised achieving an accuracy of 99.35%. After comparing the manufactured images to the initial Gravity Spy images, the authors concluded that the generated images not only recover the training set distribution very well, but it also increased the diversity among spectrograms, which is crucial for reducing overfits and to have better generalisation (Yan et.al., 2022). It is claimed in the report that the resolution of the original pictures has been scaled down, however the amount of data loss is not disclosed. Furthermore, they have not examined the accuracy of various algorithms relative to models using fake images (GAN-generated images) in this study. Similarly, there is no examination of the performance of the model if unforeseen glitches occur.

4.1. Re-generation of DeepCNN Architecture for Analysing Its Performance On Updated Dataset

We re-generated the same DeepCNN architecture used in (Bahaadini et.al., 2018) and applied it on the updated Gravity Spy Dataset. We discovered that the model is inconsistent in predicting and classifying the glitches. The accuracy has dropped from 97.69 % (the original dataset in (Bahaadini et.al., 2018)) to 88.77%. It can be seen in figure 9 that deep CNN is efficient in learning the new dataset and hence almost

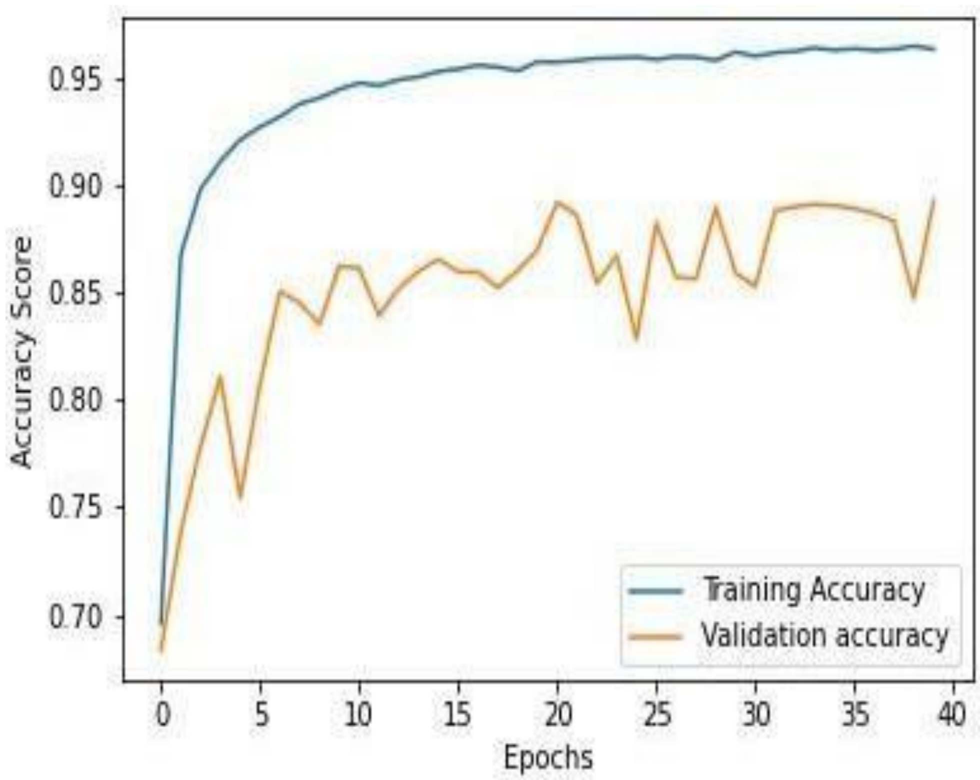

Figure 11: Training Vs Validation Accuracy using Deep Neural Networks on 31,868 images

ideal training accuracy but failed in validation phase. The work was just done on a model to show that already existing models worked well on earlier dataset but when exposed to new data they may not perform very well because of multiple unknown classes of glitches.

5. Future Scope and Conclusion

The gravity spy data can be further analysed further using other sophisticated approaches to break it down into various classes. Due to missing uniformity in sampling size ProGANs are used (Yan et.al., 2022) but it doesn't guarantee the closeness of the generated image to the real one. Usage of semi-supervised or self-supervised techniques to be used to categorise the None of the Above class of gravity spy which results in finding out more glitches. This model is not only restricted to the present data but can also be applied to new time-series data. Accuracies of varying degrees can be attained through resampling the dataset. More sophisticated data augmentation techniques can be implemented to keep track of the rate of loss. Identification of glitches paves the path to more research opportunities in the field of Astro Physics. As still many glitch classes are unknown, a model is required which can further provide a generalization and can learn that it is a glitch of some unknown type. GANs have further subvariant which can be explored and can provide a further way towards improvement for glitch classification. Other techniques or models cab further be developed in this direction. It is also required as investigated in this work, that what will be the impact of study if we remove the empty images from the dataset . Also, the glitch classes identified to have different spectrograms as per two observatories, is it giving correct study and in the correct direction or somewhere we needto explore which observatoryruns glitches to be considered or we need some other robust algorithms which can properly identify these glitches. With these questions we conclude that more proper study of data obtained from these observatories is required to be done in order to have proper analysis and classification of glitches.

6. Conflict Of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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