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# An Intelligent Hybrid Optimization with Deep Learning model-based Schizophrenia Identification from Structural MRI

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**Abstract:** One of the fatal diseases that claim women while they are pregnant or nursing is schizophrenia. Despite several developments and symptoms, it can be challenging to discern between benign and malignant conditions. The main and most popular imaging method to predict Schizophrenia is MR Images. Furthermore, a few earlier models had a definite accuracy when diagnosing the condition. Stable MRI criteria must also be implemented immediately. Compared to other imaging technologies, the MRI imaging method is the simplest, safest, and most common for predicting Schizophrenia. The following factors are mostly involved in the subprocess for the initial MRI image. Before calculating the length between the sample point and the cluster center, the initial cluster center of the sample is identified. Classification is done according to how far the sample point is from the cluster center. The picture is then generated once the new cluster center has been derived using the classification history and verified to match the cluster convergence condition. A grey wolf optimization-based convolutional neural network approach is offered to get beyond the limitations and find schizophrenia, whether it's hazardous or not. Many MRI images or datasets are analyzed in a short time, and the results show a more accurate or higher rate of schizophrenia recognition.

**Keywords:** Schizophrenia, Deep learning, Grey wolf optimization, MR Images, Convolutional neural networks.

## 1 Introduction

MR images are common throughout the globe [1]. The polygenic threat factor for MR images can now quantify MR images' well-established biological component. Significant illnesses, such as MR images, bipolar disorder, and severe depressive disorder, rank among the highest expensive medical conditions. In contrast to autism spectrum disorder, characterized by aberrant non-verbal interaction and psychological reciprocity, illusions or delusional thoughts are a frequent symptom of MR images. MR images, often known as schizophrenia, is a serious mental illness caused by structural and functional brain abnormalities that, over time, lead to problems in cognition, emotions, and behavior. The development of automated methods and methodologies for the early diagnosis of schizophrenia utilizing DL as well as MRI data has been made possible by the work of numerous researchers. Additionally, some incidences of savant syndrome among autism spectrum disorder people with amazing talents like painting have been documented. Although neurological, genetic, and ecological variables have been put out as potential causes of both illnesses, it is still unknown what the fundamental cognitive processes are. These factors' heterogeneity and non-specificity present a significant diagnostic problem. When something is heterogeneous, it signifies that various participants' symptoms, prognoses, and therapy outcomes vary greatly. MR images and autism spectrum disorder have the traits of being perceptually unusual and causing social communication difficulties. While MR images are often identified in grownups, albeit in extremely exceptional instances, they can arise throughout growth, unlike autism spectrum disorder, which usually manifests in a young life. It has also been proposed that some schizophrenia patients may fall on the autistic spectrum due to a similar neurological basis seen in both diseases. The parallels between the two disorders are so great that both exhibit abnormal sensorimotor integration as well as perceptual interpretation. But these illnesses also differ dramatically from

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one another.

There is ample evidence that maternal anxiety and initial disorders enhance the likelihood of MR images. Additionally, it has demonstrated a connection to severe emotional disorders. The influence of prenatal stress, health conditions, and obstetric problems on the emergence of serious psychological disease in MR images spectrum disease. Infection during pregnancy, nutrient deficiency, preterm birth, obstetric problems, maternal stress, perinatal issues, social hardship, urban childhood, cultural minority position, childhood abuse, harassment, traumas, and cannabis use while adolescents are only a few ecological health issues that have been linked to the development of serious mental illness. It is possible that maternal experience of mental trauma during the early or later stages of pregnancy contributed to sensitive mind growth. It is generally established that prenatal anxiety affects the placenta's ability to protect the developing fetus as well as the hypothalamic-pituitary-adrenal axis' ability to operate [2]. Maternal depression has an impact on the fetal transcriptome as well as its impact on stressed hormones. The epigenetic process relates ecological variables to changes in genetic expression in the pathophysiology of MR image illness.

MR images significantly shorten life expectancy, and the trend has not changed in recent decades. Regarding fecundity or reproductive fitness, schizophrenic victims have a very low chance of starting a family. Antipsychotics are incredibly efficient at what has been created to do, which is to lessen psychosis. Thus, the answers are not inefficient. MR images have symptoms. The dorsal striatum is implicated in the pathophysiology of MR images, and the mesolimbic theory is called into query by the unexpected discovery that dopaminergic impairment in MR images is highest within nigrostriatal pathways as a result of advancements in neuroimaging technology. At the same time, new theories of how striatal dysfunction might influence MR image symptoms have been proposed as a result of advances in the understanding of striatal architecture and functioning. Positive signs like hallucinations and delusions, together with negatives and cognitive ones like flattened mood and lack of drive, are all part of the illness known as MR images. Many hypotheses that try to describe the methods underpinning the signs of MR images are predicated on dysregulated dopaminergic regulation of striatal activity [3]. Additionally, all approved pharmaceutical therapies for MR images have an impact on the dopamine system. Despite the fact that a number of antipsychotic drugs have been suggested to work through different non-dopaminergic pathways, like the serotonergic system, all of these medications still bind to dopamine receptors, and there is no obvious correlation among effectiveness as well as serotonergic effect.

Compared to how the condition was previously understood, MRI images have undergone significant change. Now that we are aware of it, MRI images have a complex etiology that involves both gene predisposition and ecological factors. Ecological factors such as issues with pregnancy as well as delivery, childhood trauma, immigration, social isolation, urbanization, substance abuse, acting alone and in fusion across time at various levels have an impact on the likelihood that a person may contract the illness. And now know much more about the condition because of investigations on gene-environment as well as environment-environment interactions, ecological elements, and the creation of a genetic risk rating for MRI images [4]. Later, more data was accumulated that links the dopamine system to the pathogenesis of MRI images, while t is still true that all approved first-line therapies for MRI images work mainly by inhibiting the dopamine D2 receptor. Nevertheless, despite the crucial role which dopamine plays in the comprehension of MRI images, it is also grown more evident that the malfunction of the mechanism may not be enough to describe a number of occurrences. Particularly, dopamine blocking is unsuccessful in treating both cognitive and behavioral problems, and it frequently makes positive symptoms substantially worse. Schizophrenia, which affects roughly the global population, is one of the most prevalent psychiatric diseases. There may be behavioral, memory, and attention problems in MR image patients. Currently, the diagnosis of MRI images is based on a systematic analysis of the patient's self-reported experiences and actual mental illnesses, which makes it impractical to identify the condition at an initial stage. The machine-learning approach could aid in the diagnosis by identifying diseases depending on neurophysiological signals, as well as in the prognosis of illness onset [5]. According to research papers that have been published, a machine-learning technique may be able to identify tiny abnormalities in MRI Images' early stages. Differentiating between MRI image patients and healthy individuals was made possible by feeding various variables into machine-learning methods. In the initial studies of MRI image detection, volumetric characteristics and tissue density characteristics were retrieved from the grey matter, white matter, and cerebrospinal fluid regions. The functional connection has become the main focus of the inquiry. Functional dysconnectivity between many brain regions is a characteristic that has been observed according to functional interconnectivity in people with MRI images.

The disorder's diagnostic clinical symptoms often manifest in the latter half of the second and third decades of one's life, with the estimated age of onset usually occurring around five years sooner in boys than in girls [6]. The exact causes of MRI images are still unknown, despite the reality that it affects many people worldwide. Numerous research has concentrated on figuring out which biological as well as ecological factors, independently or together, may be responsible for the condition. The body is especially complicated, full of both intriguing initial observations and follow-up research that disproves discoveries of genetic associations or ecological factors. These seeming contradictions may, in reality, be a reflection of the complicated character of MRI images, which is characterized by the commencement of the illness in initial adulthood and a duration of progression with very mild degenerative alterations. MRI images are caused by a variety of seemingly inconspicuous brain disorders. The clinical state known as MRI images may be the endpoint of numerous distinct pathogenetic pathways, similar to several other human disorders. Biological methods that have their roots in developmental processes taking place before the beginning of clinical signs have been proposed in an effort to create a coherent theory of the causation of MRI images.

MR images and bipolar disorder have always been seen as opposite conditions. The anatomical alterations in the brain between the two illnesses may not be comparable as a result. However, mounting evidence indicates that MR images and bipolar illness share pathological components [7]. It contains data showing that the two diseases co-aggregate in groups and that susceptibility genes are shared. Infection exposure during pregnancy, nutrient deficiency, preterm birth, obstetric complications, nurturing anxiety, perinatal complications, social stigma, urban upbringing, racial minority behavioral standing, early life abuse and neglect, harassment, traumatic experiences, and cannabis use during childhood are just a few environmental significant threat elements that has been related to the advancement of serious psychological sickness. However, knowledge of the precise mechanisms responsible for creating these structural impairments is still lacking. Furthermore, overlapping brain networks have been suggested by theoretical methods of the functional anatomy of MRI images and bipolar disorder. Recently, it has been repeatedly documented that SZ sufferers have structural brain abnormalities, especially in the thalamus, corpus callosum, middle temporal gyrus, and middle frontal gyrus. There are various MRI images subtypes; Paranoid MRI images, Hebephrenic MRI images, Catatonic MRI Images, Undifferentiated MRI images, Residual MRI Images, Simple MRI Images, and Unspecified MRI images as shown in Fig. 1. It is a set of mental illnesses that are connected and share some characteristics. It interferes with your perception of reality also alter your thoughts, emotions, and behaviors.

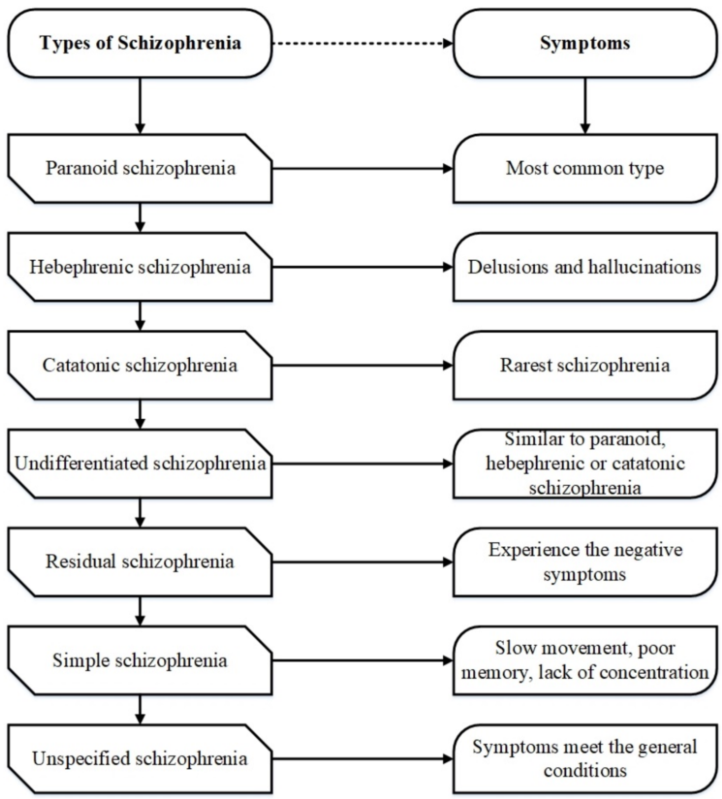


**Fig.1.** Types of MR Images.

The proposed paper's contributions are given below:

- At the beginning MRI datasets are collected from various number of schizophrenias affected patients, and the collected MRI Images are focused to estimate the existence of schizophrenia with computed tomography.
- The collected MRI Images are depicted that it has contain schizophrenia nodules, which are filtered using Wiener filter.
- Segmentation process of this research to find out the affected region of schizophrenia has been figured out with Fuzzy C-Means clustering method.

- The novel Krill Herd and Grey Wolf Optimization is used for feature extraction.
- The KHGWOCNN classifies the benign and malignant ovarian nodule.
- The process of the suggested model is reliable for the contemporary world to approach to demonstrate its value.

The document of the proposed paper is classified as follows: Section 2, reviewed some of works done on the same subject. Section 3 provided with the information regarding the problem statement. Section 4 is dealt with the detailed proposed KHGWOCNN architecture. The section 5 provided with the discussion, results and the comprehensive progress of the suggested approach to current best practices. The last section is 6, where the paper is completed.

## 2 Related Works

Dafa Shi et al. proposed machine learning based MR images prediction using structural and functional neuroimaging. MR images, a serious mental illness, is difficult to diagnose [8]. A growing range of research have discovered that multifunctional brain datasets, when combined to functional and structural MRI, can improve diagnosing accuracy when employed to investigate both functional and structural abnormalities of the individual mind. With great accuracy, machine learning is frequently employed to diagnose neurological and psychiatric disorders. The standard ML, that concatenated the characteristics into a larger feature vector, could not, however, mix diverse features from various modalities with adequate efficacy. There are several research have examined the application of global signal regression in machine learning for the diagnosis of neurological illnesses because of disagreements over its use. In this study, fMRI and sMRI data were used to carry out a novel method known as multimodal imaging and multilevel characterization utilizing metaclassifier to classify SZs and healthy controls as well as to investigate the function of GSR in SZ categorization. However, the method's classification accuracy was only 83.49% without the GSR as well as the Brainnetome 246 atlas. Additionally, it was found that models lacking GSR had greater specificity and accuracy than models with GSR. According to the results, the M3 approach can effectively separate SZs from HCs and can be used to pinpoint discriminative brain regions that can see SZ in order to study the neurological mechanisms behind SZ. The global signal might hold crucial neuronal data that can increase the precision and specificity of SZ identification.

In order to identify abnormal brain regions in MRI images, ZhiHong Chen et al. proposed using structural MRI in conjunction with machine learning [9]. It has various advantages and can serve as a reference for the medical identification of MRI images to use neuroimaging and ML to distinguish MRI images cases from healthy controls and to find aberrant brain regions in MRI images. Here, the structural magnetic resonance imaging scans from SZ patients and NCs were used in a discriminative analysis. The study suggested an ML framework that is based on selecting features from coarse to fine. The proposed framework originally introduced two-sample t-tests to identify differences, and used the recursive feature elimination (RFE) to even further eliminate unnecessary and redundant features, and at last used an SVM to learn decision models using particular features from both the white matter (WM) and grey matter (GM) of the brain. Previous research cannot be broadly applied since it has a tendency to reflect differences at the group level rather than the individual level. The strategy suggested in the study offers a greater recognition rate than earlier methods and extends the diagnostic to the individual level. The study's testing results demonstrate that the proposed framework can distinguish between schizophrenia patients and NCs, with the highest level of classifying accuracy attaining over 85%. The discovered biomarkers agree with earlier literature-based conclusions. The suggested framework can be used to diagnose additional diseases as a general approach.

According to Manan Binth Taj Noor et al. deep learning methodology could be used to analyse MRI scans to identify neurological disorders such as MRI images, Parkinson's disease, and Alzheimer's disease. The ability to forecast and treat a variety of neurological conditions, such as Alzheimer's disease, Parkinson's disease, and MRI images, is made possible by advancements in high-speed computer techniques and an extraordinary development in the generation of novel DL-based algorithms and models. The three most common neurological disorders have been identified from the MRI scan data using the most common DL approaches. There have been provided DL approaches for classifying neurological illnesses that have been documented in the literature. Future trends and unresolved issues have been discussed. The primary finding of the study was the extensive use of convolutional neural network in the diagnosis of Parkinson's and Alzheimer's disease. From the other side, DNN has been used more frequently to detect MR images. Datasets have been extensively studied concurrently for AD, PD, and SZ, respectively [10]. The comparative performance analysis of several deep learning algorithm across multiple disorders and imaging modalities, the CNN outperforms other approaches. Several current research issues are identified toward the conclusion, along with several potential future study directions.

Hooman Rokham et al. used an enhanced machine learning technique to identify the mental health of patients. A new classification-voting filtering method was developed to remove label noise, such as noisy, incorrectly identified subjects, from the structural MRI image dataset. Insightful patterns were presented, allowing for additional analysis and the model-based reassignment of labels to identified mislabeled subjects. For sets of noisy data, the proposed approach also offers potential labels. The technique is centered on computing m inner SVM classifiers, each of that is trained and evaluated by cross-validation. Additionally, the researchers used SVC from the scikit-learn python library and used a one-versus-all technique, which involves fitting one classifier for each class against all other classes. These m SVM models were being used to identify participants that were incorrectly categorized for various cross-validation sets. The study's simulations confirm our hypothesis that one effect of label noise is a decline in model performance and accuracy. The fundamental patterns we are seeking to find may be interfered with by label noise. The assertion that label noise obscured the underlying patterns is supported by the study of actual data. The 2D projection utilizing the original labels reveals that no two subjects within groups share any commonalities. The refutes the idea that there is a connection between probands who are members of the same group. As a result, the SVM classifies each person m times for k cross-validation cycles, adding up the classification votes [11]. Consensus voting was utilized by the researchers to ascertain whether a dataset has a noisy label based on the predicted labels if any voting labels were incorrect.

In order to identify MRI images in a person, Du Lei et al [12]. integrated machine learning with multi-modal neuroimaging. A severe mental illness called MRI images is accompanied by both anatomical and functional abnormalities of the brain. Recently, there has been a rise in interest in using machine learning techniques to neuroimaging data to determine a disease's diagnosis and prognosis. Although the multimodal aspect of the illness has not been taken into account, the great majority of research that have been published to date used the structural or functional neuroimaging data. From patients who had MRI images, research facilities gathered structural MRI and resting-state functioning MRI data. To discriminate the individuals at the individual level using each individual characteristic as well as their combination, a SVM classifiers were generated on each dataset separately. The performance of the model was evaluated using 10-fold cross-validation. More accurate classification is possible with functional data than with structural data. The use of images and matrices within each modality enhances performance, leading to average accuracy rate of 81.63% for data sets and 87.59% for data obtained. The best level of classification accuracy (90.83%) is achieved by using all available structural and functional metrics together. Conclusion: A promising avenue for the development of physiologically informed diagnostic tools for MRI images is the integration of multimodal measures into a single model.

Shile in [13] suggested applying a joint assessment of connected various functional networks with structural covariation to MRI images. There is mounting proof that the field is concentrating more on the integration of multimodal datasets than on utilizing a specific brain scan modality to investigate its relationship to physiological or clinical factors. Most modern multimodal fusion algorithms that employ functional magnetic resonance imaging are, however, restricted to second-level 3D features rather than the original 4D fMRI data. The price of the compromise is that the fusion process does not utilize the vital temporal data. Further, an unique method known as "parallel group ICA+ICA" has been presented to merge temporal fMRI data from group independent component analysis into a framework of independent component analysis (ICA). With this method, connected functional network variability as well as structural covariations that can be detected by other modalities can be clearly merged with first-level fMRI characteristics. According to simulation results, the proposed technique can detect intermodality relationships both strongly and weakly. In addition, a pair of fMRI-sMRI elements was discovered to be significantly connected when used with real data, and MRI images including controls both in modalities exhibited group differences. A separate cohort can have the same relationship. Finally, scores across a number of cognitive domains can be predicted using the properties discovered in the linked element pairing by the provided method. Specifically show how these multimodal brain traits can predict different cognitive scores in a different cohort. Results demonstrate that simultaneous GICA+ICA can assess joint data from both 4D and 3D data without wasting a significant amount of information up front. The approach may be used to find imaging biomarkers to research brain illnesses.

In order to identify differences in fourteen brain structural volumes in MRI images, Susan S. Kuo et al. performed a thorough meta-analysis. Despite several structural MRI studies showing that MR imaging patients have smaller average brain volumes than controls, little attention has been paid to group differences in the variance of brain volumes. Understanding the variety of MR images and interpreting mean group differences in brain size may be made easier by looking at variability. 13 constructions with medium to large mean effect sizes, including the caudate nucleus as a control structure, intracranial volume, total brain volume, lateral ventricles, third ventricle, overall grey matter, frontal grey matter, prefrontal grey matter, temporal grey matter, superior temporal gyrus grey matter, planum temporal, and insula—were examined in a meta-analysis of 246 MRI studies. In comparison to controls, there were no discernible variations in the variability of cortical/subcortical volumes in people with MRI images. As opposed to controls, MRI images was associated with higher levels of intracranial variability, particularly in the lateral as well as third ventricle volumes. These results underline the necessity of paying closer attention to the ventricles and conducting thorough investigations of the distribution of brain volume in order to better understand the pathophysiology of MRI images. Although there are still some unanswered questions regarding the significance of mean group variations in structural brain size, this study raises significant issues and offers numerous lines of inquiry for further investigation. In general, this study implies that MRI images diversity in brain structural volumes warrants further investigation. These results emphasize the necessity of more thorough investigations of MRI brain volumes distribution based on raw data to establish their form and composition, with skew as well as kurtosis for distribution of brain volumes assessed between and within groups [14]. The findings suggested paying closer attention to the origin and growth of the brains ventricles in MRI images and determining whether these mechanisms are unique to this condition or also present in other mental disorders.

## 3 Problem Statements

MRI scans will display phenomena like significant noise, misleading images, and weak borders because of how complicated the human brain's tissue structure is and because of how MRI technology works as an imaging tool. Traditional active contour models, for instance, frequently handle very noisy images prematurely and weaker boundary leakage happens when the border is smeared. Multivariate analysis has been incorporated with taxonomy to create cluster analysis. Gathering information to categorize comparable data sets is the aim of cluster analysis. The clustering outcomes highlight the links and variations within the data collection, and they serve as a crucial foundation for data processing. The earlier works on machine learning and MRI images identify the signs and assess them. To identify the MRI images between combined data sets that are both beneficial and detrimental. MRI images cannot provide a precise diagnosis. The MRI scan must be cleaned of a variety of noises, comprising movement, mean signal strength, and spatial distortions, from a variety of sources in order to assure accurate data interpretation. To tackle the limitations in this technique the enhanced deep learning approach is suggested. Here, a convolutional neural network technique based on Krill Herd and Grey Wolf Optimization is applied to predict MRI images at an early stage.

## 4 Proposed Method

In order to anticipate MRI images in its early stages, this work combines innovative Krill Herd and Grey Wolf Optimization. Magnetic resonance imaging is first used for training and testing purposes. MRI images go through a pre-processing approach that employs the Wiener filter to eliminate extraneous noise. The data set images are segmented in this procedure using the Fussy C-Means clustering technique. To identify Schizophrenia and its severity, the proposed Krill Herd and Grey Wolf Optimization strategy is used. To operate enormous datasets and obtain a superior accuracy value, a convolutional neural network is used as illustrated in Fig. 2.

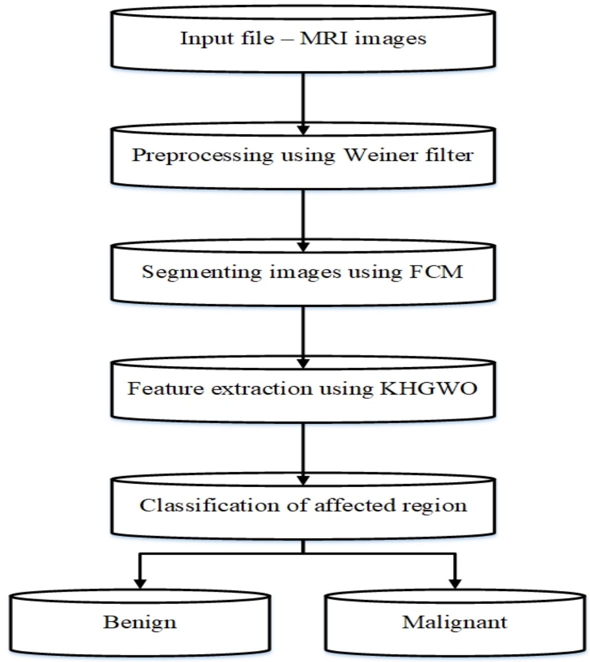


**Fig. 2:** Proposed KHGWO method.

### 4.1 Pre-processing

The magnetic resonance images are influenced by neutral and irregular noise, which lowers the sample image testing rate. The magnetic resonance images are mostly affected by noises such as, Rician noise, Gaussian noise, and Rayleigh noise. In order to process any segmentation approach, the noise existing in the MRI images must first be eliminated utilizing one of several de-noising procedures, depending on the image collected. Field intensity, RF pulses, RF coil, voxel volume could all be contributing factors to the noise in MRI images. Thus, the Wiener filter is used to lessen the noise in the MRI images. By using the overall average of the nearby pixels, which is based on the Wiener distribution, the Wiener filter is used to replace the noise from the image in the representation. The Wiener filter is used because it is found to be particularly effective. The linear filter known as the Wiener filter, on the other hand, is used to blur the noise in an image. The noises in the depictions must be minimized in order to produce a satisfactory MRI images depiction. The noise-reduced images are thus used by the convolutional neural network model centered on the Krill Herd and Grey Wolf to discriminate between benign and malignant schizophrenia nodules.

The equation for Wiener filter is given as,

$$w(k, l) = \sigma^2[n - a(k, l)] \quad (1)$$

Here, $\sigma^2$ is the difference of Gaussian noise, k and l are pixel size of per image, n is the noise characteristics.

### 4.2 MR Image Segmentation using FCM

The following factors are mostly involved in the subprocess for the initial MRI. Prior to calculating the radius between sample point as well as the cluster center, the initial cluster center of the sample is identified. Things are characterized using the length between sample points and the cluster center. Following that, the new cluster center is generated using the classification history, and then it is determined whether this meets the cluster convergence requirement before the picture is output.

In MRI figure images, the afflicted region is often segmented using the segmentation technique. The result of image processing is determined on how well the segmentation procedure worked. In clinical image processing, picture segmentation's primary goal is to locate any nodules present in MRI images and to produce sufficient data to enable further detection. Here, a sophisticated Fussy C-Means clustering is utilized to segment the MRI images. Furthermore, clustering is regarded as a common unsupervised method for categorizing homogeneous datasets into groups based on their features. Additionally, various approaches to this process are provided in order to enhance the activation of the conventional FCM clustering. Benefits of FCM include compatibility with a person's analytical abilities, ease of execution, brevity in explanation, and effective segmentation. In the segmentation of magnetic resonance images, fuzzy c-means also produced improved segmentation results. Segmentation is often used to recognize problems with an image's curves and lines as well as its limitations. Segmentation separates the images into sets of pixels and annotates the pixels within each group.

FCM clustering, the method recommended in this paper to identify the precise damaged region in MRI. MRI images are used in the segmentation process, which was started by the FCM clustering, and its application in the aforementioned point is in the following eqn. (2),

$$F_m(\mu, a) = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ji}^{m} ||x_i - a_j||^2 \tag{2}$$

Utilizing the geographical labelling and morphological processes described in the formula, the fat region is removed (3). As is customary in the regular FCM, the cluster centers are chosen at random.

$$p_i = \sum_{j=1}^{N} q_{ij} \, (a_i(r_j))^M x_j / \sum_{j=1}^{N} q_{ij} \, (a_i(r_j))^M \tag{3}$$

The adaptive weights are calculated using Riemann distance between the measurement source rj as well as the updated cluster center pi, and are represented by the expression q ij=‖ r j- p i‖. The idea of adaptive weights assigns the equally distant pixels to a cluster by taking into consideration the length of the pixel nearest to the predicted decision border. Another finds that when the language fuzzifier (M) is employed to determine the membership values, the cluster centers are more accurate. Additionally, this establishes the cluster centers at positions that are more accurate than those of the traditional FCM in the setting of noise and IIH.

The MR image also shows tissues from the ovary and other places. In the tissue's region segmentation stage, the damaged portion is then removed once the non-schizophrenia tissue region has been removed. The fat region is removed using regional labelling and morphological techniques, as was previously mentioned. The next clustering method is one based on the FCM algorithm. First, the language fuzzifier output is calculated using the algorithm,

$$\mathrm{B} = \cup_{\propto \in [0,1]} \propto / F_M(\propto) \; where \; F_M(\propto) = [F_M^L(\propto), F_M^R(\propto)] \tag{4}$$

Further cluster centers randomly declared. The type two using, member values are updated,

$$a_i(H_j) = \cup_{\propto \in [0,1]} \propto / [a_i^L(H_J \,|\propto), a_i^R(H_j |\propto)] \tag{5}$$

And thus, the cluster centers are updated. The strategy for improving it using conditioned modes iteratively is utilized. The technique gives a group of pixels that are evenly separated apart each cluster decision boundary. The noise performance of the proposed model is enhanced by the adaptive spatial information of the surrounding pixels. The stopping condition is the value of the minimum fitness function improvement. Researchers can, however, use the maximum number of iterations as a substitute criterion. Clusters have been created from the MRI images that have been submitted. Each pixel holds three membership values. The defuzzification procedure is used to extract the tissues sections from the membership matrix. A pixel is assigned to the cluster node where it has the highest membership value.

## *4.3 Combined KHGWO Algorithm for Feature Extraction*

### *4.3.1 Krill Herd Optimization Algorithm:*

The krill herd algorithm replicates the characteristics of krill, which contribute to movement based on fitness for each individual in the herd. It represents a novel method for intelligent swarm optimization. Depending on how fit it is, each Krill herd contributes differently to the moving process. Additionally, it depends on whether the neighboring Krill inhabitants have a mutual local seek mechanism that acts as an enticing or deterrent force. The majority of the features of the Krill herd are dietary in nature. They look into it while also getting something out of it. Less parameters can be used to design krill behavior to find the world's best answer, whose decision is believed to be the outcome of the Krill patient's degree of fitness,

$$\hat{G}\, p.q = \frac{G_p - G_q}{G^{worst} - G^{best}} \tag{6}$$

$G^{worst}$ and $G^{best}$ are the fitness values of the greatest and worst Krill individuals, $G_p$ is the fitness of the $i_{th}$ Krill individual, $G_q$ is the fitness of the $j_{th}$ neighbor, z is a tiny positive number to prevent singularities, and N is the total number of neighbors.

### *4.3.2 Grey Wolf Optimization Algorithm:*

It is a swarm-based method in a sense. It imitates the grey wolf's herd behavior and stalking behavior, as previously stated. In nature, the grey wolf leads a life of hunting and social leadership. Grey wolves typically work in packs of 5 to 12 individuals. There are four different kinds of wolves in a pack: α, β, γ, and $\omega$. They are dispersed according to the degree of dominance. While the β has the least control over the pack, the α has more. The widest member of the pack, γ, will manage and make decisions for the group. This has the power to lead the group when hunting and has authority over it. γ, the pack's third-level dominator, utilized to assist, protect, and watch over the group's members, especially the frail and elderly wolves. $\omega$, the remainder of the pack, is the last set. The hierarchy gave the wolves orders to circle and pursue their prey. The stalking action entails tracking down the prey, surrounding and intimidating the prey to restrain its movement, and then eventually attacking the victim. The following equations can be used to mathematically develop this strategy of encircling the victim:

$$\vec{V} = |\,\vec{D} \times \vec{X}_S(l) - \vec{Y}(l)| \tag{7}$$

$$\vec{X}(l+1) = \vec{X}_s(l) - \vec{K} \times \vec{V} \tag{8}$$

$$\vec{K} = 2 \times \vec{c} \times \vec{u}_1 - \vec{c} \tag{9}$$

$$\vec{D} = 2 \times \vec{u}_2 \tag{10}$$

$$b = 2 - k \times \frac{2}{L} \qquad ;(11)$$

Where $\vec{Y}_s(l)$ is the position of the prey at iteration k, $\vec{Y}(l)$is the position of the wolf at iteration l and (l + 1), respectively, K and D are 2 regression coefficients, and L seems to be the highest number of iterations. Avoiding local minimum stagnation and striking a balance between supply and demand are the main objectives of D and K, respectively. By altering the value of D at random, grey wolf optimization can prevent local optima stagnation and is also capable of exploiting and explore a specific search space if, respectively, |K | 1 and |K |> 1. Each iteration should update the H level solutions depending on the E and F level solutions.

$$\vec{V}_E = |\,\vec{D}_1 \times \vec{Y}_E - \vec{Y}\,| \tag{12}$$

$$\vec{V}_F = |\,\vec{D}_2 \times \vec{Y}_F - \vec{Y}\,| \tag{13}$$

$$\vec{V}_G = |\,\vec{D}_3 \times \vec{Y}_G - \vec{Y}\,| \tag{14}$$

$$\vec{Y}_1 = \vec{X}_E \times \vec{K}_1 - \vec{V}_E \tag{15}$$

$$\vec{Y}_2 = \vec{X}_F \times \vec{K}_2 - \vec{V}_F \tag{16}$$

$$\vec{Y}_3 = \vec{X}_G \times \vec{K}_3 - \vec{V}_G \tag{17}$$

$$\vec{Y}(l+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{18}$$

The Combined equation for Krill herd and Grey wolf is given as,

$$\hat{G}\,p.q = \frac{G_p - G_q}{G^{worst} - G^{best}} + \vec{Y}(l+1) \tag{19}$$

The feature extraction is done with eqn. (21). Where $G^{worst}$ and $G^{best}$ are the fitness values of the greatest and worst Krill individuals, G i is the fitness of the ith Krill individual, G j is the fitness of the jth neighbor, Where $\vec{Y}_s(k)$ is the position of the prey at iteration k, $\vec{Y}(k)$ is the position of the wolf at iteration k and (l + 1).

### *4.4 Convolutional neural network (CNN)*

Utilizing convolutional neural network classifiers, the nodules of MRI Images are identified. It efficiently assesses the MRI representation and acquires the necessary qualities thanks to its multi-layered construction. The representation input layer, the convolution layer, the Max pooling layer, the fully connected layer, and the output layer are the four layers that make up a convolutional neural network classifier. Prior to the training phase, the convolutional neural network modifies the intensity values of its representation pixel. The model that trains the most quickly is CNN. The size of the input MRI representation should be uniform. The equation for each representation in the training dataset is given in eqn. (20)

$$Q(r,s) = \frac{o(r,s) - \mu}{\sigma} \tag{20}$$

a) Convolutional layer

The convolutional layer uses each layer to examine each representation's complexity after gathering a range of images as input. It is directly connected to the characteristics we look for in the given image. It's expressed as an eqn. (21)

$$f_h^p = x\left(\sum_{j \in N_h} f_j^{p-1} * Q_{jh}^p + r_h^p\right) \tag{21}$$

$N_h$ – It denotes an input option. It has been specified that the output is an additive bias s. When the summation of the maps r and s over map h, the kernel is applied to map h.

b) Max pooling layer

The downsampling layer's fitting and neuronal size are reduced using this layer. The number of parameters, speed of calculation, and size of the feature map, training time, and overfitting are all decreased by the pooling layer. Using a calculation (22), overfitting is calculated and is characterized as 50% on test data and 100% on training dataset.

$$x_{mab} = max_{(u,v)\in} f_{pcd} \quad (22)$$

The map $f_{puv}$ is the component shown as (u, v) that within pooling region points, which depicts the neighborhood in and around the location (r, s).

c) Fully connected layer

The context for representation classification uses a fully connected layer. Before FC layers, convolutional layers are placed first. Using the FC layer, the output as well as input illustrations are mapped. The final levels of the network are made up of layers that are completely connected. The FC layer's input comes from the max pooling layer's output.

d) SoftMax layer

Using SoftMax layer, the scores are converted into normalized ratio distributions. The result is given to the classifier as an input. A SoftMax classifier uses the SoftMax layer's structure to MRI images nodules and is a type of standard contribution classifier. In eqn. (23), it is shown.

$$\sigma(\vec{Z})_a = \frac{e^{x_a}}{\sum_{h=1}^{p} e^{x_h}} \quad (23)$$

## 5 Results and Discussion

This section includes the findings of the suggested approach as well as comparisons of the noise removal from Magnetic Resonance Imaging (MRI) using the new filter, segmentation utilizing Fuzzy C-Means clustering, and feature extraction using a combination of KHGWO optimization detection methods. Trials of the suggested method's approach have been run, and the results have been compared to those of the segmentation and diagnosis methods. The tests were assessed using MRI, and the paper demonstrated the efficacy of the strategy. The paper demonstrated how the suggested model differed from the earlier approaches. The datasets from brain MRI experiments have been used in this study. To distinguish MRI images from harmful and harmless datasets, a hybrid KHGWO convolutional neural network is deployed. Performance measures including Precision, Accuracy, Recall, and F-measure are used to evaluate the presentation of the proposed approach.

### *5.1 Accuracy*

Accuracy calculates the precise working of the approach. Typically, it is the proportion of correctly recognized perceptions to all perceptions. Accuracy is declared in Eqn. (24),

$$Accuracy = \frac{T_{Pos}+T_{Neg}}{T_{Pos}+T_{Neg}+F_{Pos}+F_{Neg}} \quad (24)$$

### *5.2 Precision*

Precision is determined by counting the percentage of accurate positive tests that can be retrieved from the total numbers of positive tests. Using Eqn. (25), it is possible to determine the percentage of a precise study,

$$P = \frac{T_{Pos}}{T_{Pos}+F_{Pos}} \quad (25)$$

### *5.3 Recall*

The percentage of overall positive and negative prediction accuracy to positive prediction accuracy is referred to as recall. In the study, which is given in Eqn. (26), it shows what ratio of forecast we were exact about.

$$R = \frac{T_{Pos}}{T_{Pos}+F_{Neg}} \quad (26)$$

*5.4 F1-Score*

The estimation of the F1-score combines recall and precision. The estimation of the F1-score, which is denoted in Eqn. (27), is evaluated in terms of precision and recall.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \quad (27)$$

**Table 1:** Performance evaluation based on KHGWOCNN.

| | CNN | KHGWO |
|---|---|---|
| Training accuracy | 99.2 | 99.5 |
| Testing accuracy | 99.3 | 99.6 |

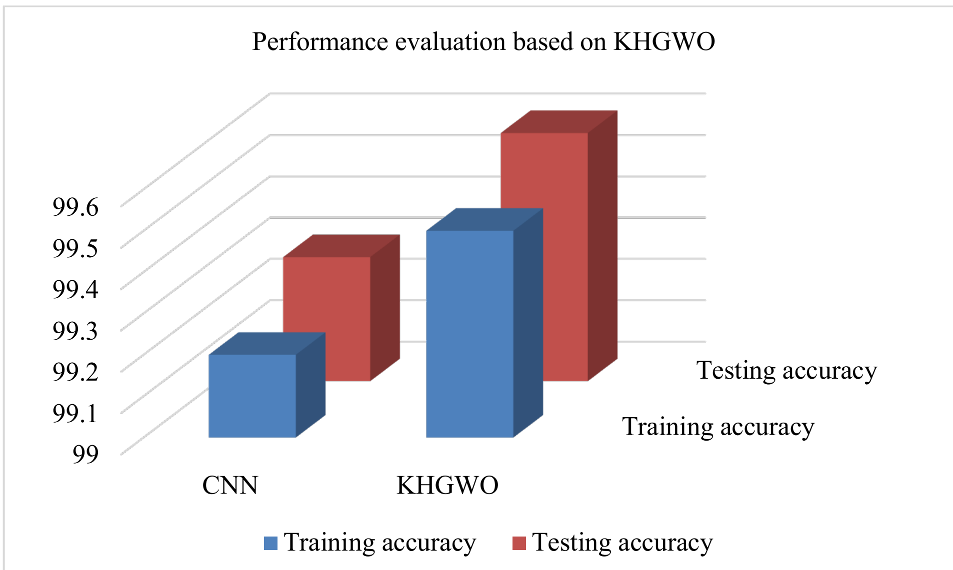


**Fig.3.** Performance of KHGWO Optimization

Table 1 depicts that the testing and training procedure the accuracy of the Conventional Neural Network is 99.2% and 99.3%. When utilized the hybrid Krill Herd Optimization and Grey Wolf Optimization, the accuracy of the testing and training procedure raises to 99.5% and 99.6% respectively. Fig. 3 portrays the operation analysis with the optimization and without optimization.

**Table 2.** Comparison of Accuracy.

| Method | Accuracy |
|---|---|
| Structural MRI | 97 |
| Multi-kernel Capsule Network | 82.42 |
| LOOCV | 83.49 |
| SVM | 75.11 |
| Proposed KHGWO | 98.9 |

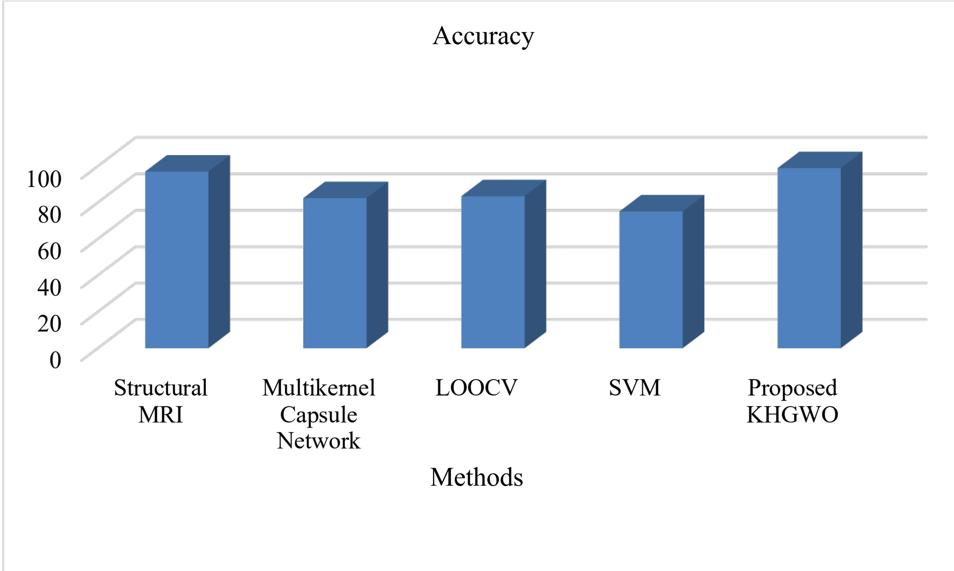


**Fig.4:** Comparison of Accuracy.

The utilized combined novel Krill Herd and Grey Wolf based CNN gains higher accuracy while comparing with the already existing MRI images predicting methods such as Structural MRI, Multi-kernel Capsule Network, LOOCV classifier, and SVM classifier are showed in the table 2. Fig. 4 portrays the accuracy between KHGWO and other methods.

**Table 3:** Comparison of Sensitivity and Specificity.

| Method | Sensitivity | Specificity |
|---|---|---|
| Structural MRI | 81.6 | 47.1 |
| Multikernel Capsule | 88.57 | 75.00 |
| LOOCV | 0.05 | 0.001 |
| DGM | 87.4 | 82.2 |
| Proposed KHGWO | 95.1 | 96.2 |

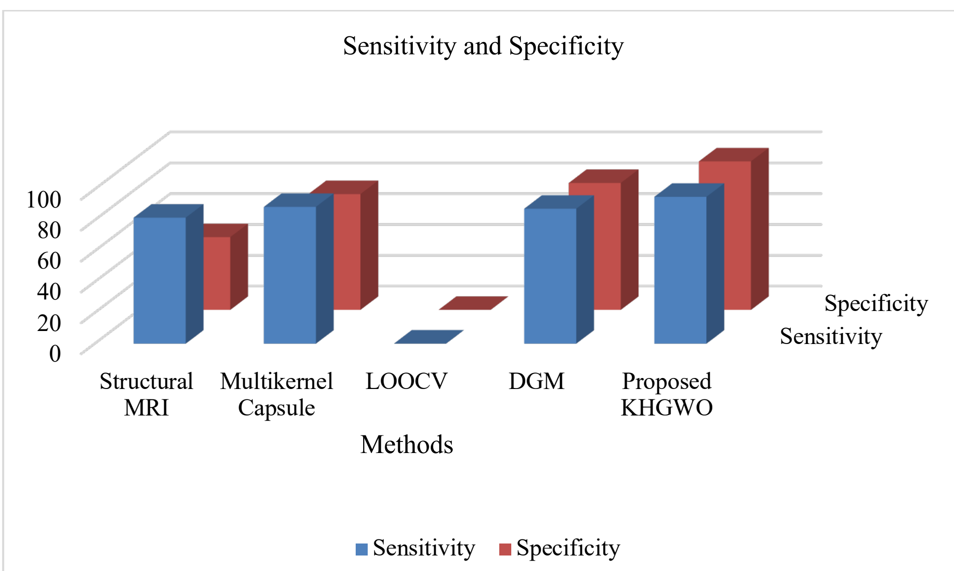


**Fig. 5:** Comparison of Sensitivity and Specificity.

Table 3 depicts that the proposed technique of combined Krill Herd and Grey Wolf based CNN achieves higher Sensitivity and Specificity of 95.1% and 96.2%, comparing to the existing Schizophrenia prediction techniques such as

Structural MRI, Multi-kernel Capsule, LOOCV and DGM. The advanced KHGWO-based Convolutional Neural Network gives better accuracy than the performance evaluated by employing Convolutional Neural Networks separately. Here the achieved accuracy level 98.9% using the KHGWO method. This indicates KHGWO depends on Convolutional Neural Network that can identify MR images earlier. Fig. 5 depicts the Comparison of Sensitivity and Specificity between KHGWO method and other methods.

The paper discusses how to predict MRI images using a variety of methods, including segmentation using the FCM clustering method, pre-processing with a Wiener filter, and feature extraction using a convolutional neural network that combines a new KHGWOCNN. In order to detect MRI images, a huge number of data sets comprised of magnetic resonance images (MRI) were pre-processed, segmented, and the features were extracted. An innovative technique is the Krill Herd algorithm. This is successfully coupled in a new method to foresee the issue using Krill Herd Optimization. Each candidate's purpose is to fill the gap or be similar.

## 6 Conclusions

To categorize the diseased area of any diseases in the modern world, we need more advanced technology and quick image processing. This research suggests an optimization for Krill Herd and Grey Wolf based on deep learning. This mostly seeks to discover MRI images. When segmenting magnetic resonance images, fuzzy C-Means clustering is utilised. When extracting features, a convolutional neural network is used with the Krill Herd and Grey Wolf Optimization. For increased effectiveness, CNN is utilized. The hybrid model will be improved and introduced in order to more accurately predict MRI images. The suggested KHGWO approach is assessed using a sizable collection of medical datasets. The results show that the proposed algorithm causes MRI images, which is examined in the study. The proposed value can be applied to disrupt optimization issues for future improvement. The research's maximum level of accuracy was obtained using the suggested method's results. This procedure and the variation in accuracy can be used as a guide in the future.

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