| Potential Hybrid Mode | | |
|---|---|---|
| *Model No* | *Hybrid Model Combination* | |
| 1 | ResNet50 + DenseNet101 | ResNet50 is known for its de while DenseNet201 has d scenarios. Combining these m connections of [ |
| 2 | EfficientNetB0 + DenseNet121 | EfficientNetB0 is designed densely connected archite efficiency |
| 3 | ResNet101 + MobileNetV3 | ResNet101 provides a deep a optimized for efficiency and s balance betv |
| 4 | DenseNet121 + EfficientNetB4 | DenseNet121's dense cor vanishing gradients, while Effi |
| 5 | VGG16 + EfficientNetB4 | VGG16, known for its simp modern architecture o |
| 6 | ResNet50 + VGG16 | ResNet50's depth and skip co proven architectur |
| 7 | VGG19 + EfficientNetB4 | VGG19 has deep feature ext accuracy and computatio performance |

| | | |
|---|---|---|
| 8 | MobileNetV3 + DenseNet201 | MobileNetV3 is known fo DenseNet201 has dense cor result in a moc |
| 9 | InceptionV3 + ResNet152 | InceptionV3's ability to handle deep residual learning cap cl |
| 10 | Capsule Networks (CapsNet) + ResNet50 | Capsule Networks help preser Combining this with ResNet feature |
| | | |

| *Possible Otl* | | |
|---|---|---|
| ***Model No*** | ***Hybrid Model Combination*** | |
| 1 | Capsule Networks (CapsNet) + EfficientNetB4 | Capsule Networks are desig than traditional CNNs, while E these could lead to en |
| 2 | 3D Convolutional Neural Networks (3D CNN) + DenseNet201 | 3D CNNs can capture vc comprehensive analysis c connections of Der |
| 3 | Attention Mechanisms + ResNet152 | Attention mechanisms help Integrating this with a deep r detect subtle |
| 4 | Transformer Models + EfficientNetB4 | Transformer models, known f adapted for vision tasks (e.g., EfficientNetB4 could ha |

| | | |
|---|---|---|
| 5 | U-Net + DenseNet201 | U-Net is specifically designe details in medical images. segmentation and |
| 6 | GANs (Generative Adversarial Networks) for Data Augmentation + ResNet101 | Using GANs to generate addit Training ResNet101 on thi |
| 7 | U-Net + EfficientNetB0 | U-Net is excellent for image s and accuracy. This combinati |
| 8 | Attention Mechanisms + DenseNet121 | Attention mechanisms can DenseNet121's dense conne could lea |

| H | | |
|---|---|---|
| ***Model No*** | ***Hybrid Model Combination*** | |
| 1 | ResNet-50 + VGG16 | ResNet-50 and VGG16 indiv compared to other models. |
| 2 | VGG16 + Inception V3 | Both VGG16 and Inception V combining them mig |
| 3 | Inception V3 + MobileNetV3 | Inception V3 and MobileNetV in the table. Their com |
| 4 | CNN + Inception V3 | Standard CNN models ha architectures like DenseNet not |

| | | |
|---|---|---|
| 5 | AlexNet + VGG16 | AlexNet is an older architectu<br>models like ResNet and Effic |
| 6 | 3 Layer CNN + VGG16 | The 3 Layer CNN has shown<br>might not si |
| 7 | ResNet-50 + Inception V3 | The table shows that ResNet-<br>combination might |

***RECOMMENDED HYBRID MO***

**Recommended Hybrid Model: EfficientNetB7 + DenseNet201**

Reasoning: EfficientNetB7 is known for its superior performance and efficiency in va
existing models.
DenseNet201 provides strong performance metrics in the existing table, and its der
reuse.

Justification for Recommendation: Performance Potential: EfficientNetB7 is a more
an enhanced version of DenseNet121. Combining these can leverage the strengths

Feature Extraction: EfficientNetB7's efficient scaling and DenseNet201's dense conr
mechanism, potentially leading to higher accuracy.

State-of-the-Art Models: Both models are recent and incorporate advanced techniq
achieving high accuracy.

***Additional Hybrid Model Reccomendatio***

**Model : EfficientNetB7 + ResNet152**

Reasoning: ResNet152 is a very deep network, and combining it with EfficientNetB7
enhanced performance

enhanced performance.

Justification:
Depth and Efficiency: ResNet152's depth can capture intricate details, and EfficientI

Complementary Strengths: Combining these models can take advantage of ResNet's

| ls that can be Build from Previous Research Papers | |
|---|---|
| *Reason* | *Justification fo* |
| epth and strong performance on many classification tasks, emonstrated superior accuracy and precision in various iodels could leverage the depth of ResNet50 and the dense DenseNet201 to improve overall performance | |
| for efficiency and scaling, which could complement the ecture of DenseNet121. This combination might balance and accuracy, leading to better results. | |
| rchitecture with good generalization, while MobileNetV3 is speed. Combining these models could potentially provide a ween depth and computational efficiency. | |
| nectivity can enhance feature propagation and reduce cientNetB4's efficient scaling and architecture search might further boost performance. | *Performance Metrics: Both Dense demonstrated strong performanc them leverages the dense con mechanisms, Complementary Strengths: Dense reuse and propagation, while Effici performance with Higher Accuracy Potential: Given t table, this hybrid model is likely precision, making it a suitable c* |
| licity and effectiveness, might be complemented by the f EfficientNetB4, which optimizes both accuracy and computational efficiency. | |
| nnections could benefit from VGG16's straightforward and e, potentially leading to improved performance. | |
| raction capabilities, and EfficientNetB4 offers a balance of nal efficiency. This combination could enhance overall by leveraging the strengths of both models. | |

| | |
|---|---|
| ɪr its lightweight architecture and high efficiency, while ınectivity for better feature reuse. Combining these could del that is both efficient and highly accurate. | |
| multiple scales of information combined with ResNet152's abilities could improve the model's ability to detect and lassify brain tumors accurately. | |
| rve spatial hierarchies, which is critical for medical imaging. :50's robust deep learning architecture can enhance both extraction and spatial understanding. | |
| | |

***her Hybrid Models Suggested by Sources***

| ***Reason*** | ***Justification fo*** |
|---|---|
| ned to handle spatial hierarchies in data more effectively fficientNetB4 optimizes accuracy and efficiency. Combining hanced feature extraction and better performance. | |
| olumetric information in MRI scans, providing a more of the brain's structure. Combining this with the dense nseNet201 might improve accuracy significantly. | |
| the model focus on the most relevant parts of the image. model like ResNet152 could enhance the model's ability to features, potentially improving accuracy. | |
| for their success in natural language processing, have been Vision Transformers). Combining a Vision Transformer with rness the strengths of both architectures for superior performance. | *Advanced Representation Learni their ability to capture long-ran patterns within data. This abil analysis where subtle fea EfficientNetB4's Efficiency: Effi efficiency and accuracy. Its sca model is both powerful and Hybrid Synergy: Combining Tra leverages the strengths of bo leading to higher accuracy ar Transformer can handle comple ensures efficient computatio extrac* |

| | |
|---|---|
| d for biomedical image segmentation and can capture fine Combining this with DenseNet201 could enhance both classification tasks, improving overall accuracy. | |
| tional training data can help improve model generalization. s augmented dataset might lead to higher accuracy and robustness. | |
| egmentation, and EfficientNetB0 is known for its efficiency on could improve segmentation and classification of brain tumors simultaneously. | |
| help the model focus on relevant parts of the image, and tions ensure better feature propagation. This combination d to improved accuracy and robustness. | |

| ***lybrid Models that might not be Ideal*** | |
|---|---|
| ***Reason*** | |
| vidually have shown lower performance in some instances Combining them might not yield the best results based on the provided data | |
| 3 have shown variability in their performance metrics, and ht not significantly improve accuracy or precision. | |
| 3 individually do not consistently outperform other models bination might not lead to significant improvements. | |
| ve shown lower accuracy compared to more advanced and EfficientNet. Combining CNN with Inception V3 might enhance performance sufficiently. | |

| | |
|---|---|
| ıre that generally underperforms compared to more recent cientNet. Combining it with VGG16 might not provide the best results. | |
| lower performance metrics, and combining it with VGG16 gnificantly enhance accuracy or precision. | |
| -50 and Inception V3 have variable performance, and their not result in the highest accuracy and precision. | |

***DEL***

arious image classification tasks, outperforming many

ıse connectivity can enhance feature propagation and

advanced version of EfficientNetB0, and DenseNet201 is of both architectures.

ıectivity can provide a comprehensive feature extraction

ques in deep learning, making them suitable candidates for

***ın using ChatGPT***

' could leverage the depth and efficient scaling for

NetB7's efficient scaling can handle large datasets well.

s depth and EfficientNet's optimized architecture.

| |
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| *or Best Model* |
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| *eNet121 and EfficientNetB4 have e metrics individually. Combining nectivity and efficient scaling respectively. Net121 provides excellent feature ientNetB4 is designed to maximize fewer parameters. heir individual performance in the to achieve higher accuracy and hoice for brain tumor detection.* |
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| *or Best Model* |
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| *ing: Transformers are known for*<br>*ige dependencies and intricate*<br>*lity is crucial in medical image*<br>*itures can be significant.*<br>*cientNetB4 offers a balance of*<br>*ıling method ensures that the*<br>*l computationally feasible.*<br>*insformers with EfficientNetB4*<br>*oth architectures, potentially*<br>*id better generalization. The*<br>*x patterns, while EfficientNetB4*<br>*on and high-quality feature*<br>*ction.* |