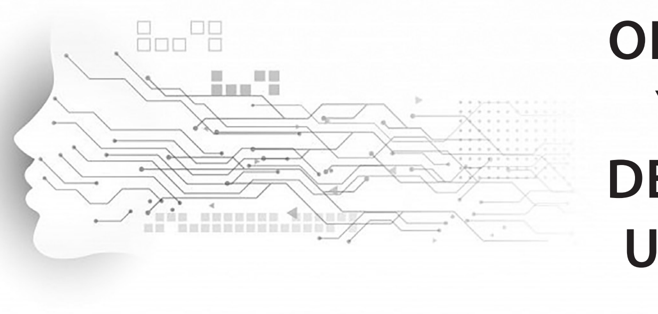
Bölüm
9



# OFTALMOLOJİDE YAPAY ZEKA VE DERİN ÖĞRENME UYGULAMALARI

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## ÖZET

Yapay zeka ve derin öğrenme algoritmaları son yıllarda tıp alanında popüler çalışma alanıdır. Oftalmoloji, tıp içerisinde teknolojinin en çok kullanıldığı bölümlerden biridir. Dünyada sık görülen göz hastalıklarının tanı, takip ve sınıflamasında bu modeller kullanılarak klinik sonuç elde edilmeye çalışılmaktadır. Fundus fotoğrafları, görme alanı testleri, optik koherens tomografi görüntülemeleri ile diyabetik retinopati, yaşa bağlı maküla dejenerasyonu, glokom, maküler ödem, optik nöropati, santral seröz koryoretinopati, prematüre retinopatisi ve retina segmentasyonu gibi konularda derin öğrenme algoritmaları üzerine çalışılmaktadır. Erken tanı ve doğru zamanda yapılacak hasta yönlendirmesi ile insanların yaşam kalitesinin artırılması ve önlenebilir körlüğün önüne geçilmesi hedeflenmektedir. Yapay zeka modelleri kullanılarak, bireylerden alınan görüntüler uzak merkezlerde işlenecek; sonucunda kişiye ne yapması gerektiği konusunda önerilerde bulunacaktır. Teletıp kavramının hayatımıza girmesi ve pratiğe dökülmesi yapay zeka sistemleri ile mümkün olacaktır. Net çizilmiş tanı kriterlerinin olmaması, görüntülerin iki boyutlu olması ve çekimlerin genellenebilir olmaması yapay zeka sistemlerinin mevcut dezavantajlarıdır. Gerçek hayatta uygulanabilmesi için doğruluk, sensitivite, spesifisite, güvenirlik ve validite çalışmalarına ihtiyaç vardır. Yapay zeka günlük pratiğe girerken etik ve hukuk çerçevesinde düzenlemeler yapılması önem teşkil etmektedir. Bu makalede yapay zeka, makine öğrenmesi, derin öğrenme sistemleri ve oftalmolojide uygulama modelleri üzerine gelişmeler özetlenecektir.

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## SONUÇ

Dünyada önlenebilir körlüğün mücadelesinde yapay zeka önemli bir noktaya gelecek gibi gözükmektedir. Erken tanı koyma ve doğru zamanda yapılacak hasta yönlendirmesi ile yapay zekanın günlük pratikte yaygın kullanıma girmesi beklenmektedir. Sağlık açısından imkanı yetersiz ve alanında uzman doktoru olmayan yerleşim yerlerinden, alanında uzman oftalmologlara aktarılacak işlenmiş bilgi, yapay zeka sayesinde olumsuz sonuçlar doğurmadan toplum sağlığını koruyacaktır. Bu akıllı sistemler hayatımıza girerken etik ve hukuk çerçevesinde düzenlemeler yapılması, yapay zeka kaynaklı ortaya çıkabilecek sosyal sorunların önüne geçmesi açısından önem arz etmektedir.

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